Diversification of Wind and Solar Energy Portfolio Risk

An Explorative Analysis for Germany 2010-2012

DISSERTATION

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The University of St. Gallen, School of Management, Economics, Law, Social Science and International Affairs hereby consents to the printing of the present dissertation, without hereby expressing any opinion on the views herein expressed.

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The President:

Prof. Dr. Thomas Bieger

PREFACE

My personal goal to write a dissertation is achieved. It was a very challenging project during my regular full time job but also an insightful adventure into academia. I am glad I had the opportunity to experience this time but I would not have been able to complete this exciting journey without the help of all my friends. Many people supported me along the way and I want to thank all of them for their encouraging words and advice, proof-read abilities and distraction strategies.

First, I would like to thank my doctoral advisor Prof. Dr. Wüstenhagen for the opportunity to pursue my doctoral degree as an external student at the University St. Gallen. I am very grateful for the fruitful encouraging discussions and the openness to tread a new path in an area of little research. His trust in my work grouped with his guidance enabled an out of the box approach to gain further insights on a topic relevant to future managers and policy makers. I also want to express my gratitude to Prof. Dr. Frauendorfer, who agreed to supervise this study in the role of co-advisor. His valuable input on modeling further increased the robustness of the results.

Second, my gratitude especially goes to my friend Sina who helped me to overcome hurdles by valuable conversations and intense discussions associated with the research project. This enabled me to keep up my self-discipline even in times of mental imbalance. Moreover, I want to thank Melanie who inspired and helped me to keep up my motivation. Thank you Beate, Nadja and Katrin for supporting me during the highs and lows, especially in the beginning and the end phase of this research project.

In spite of many sleepless nights, I want to encourage all of you. Only those who experience their individual boundaries are able to appreciate every single day of this beautiful life.

I dedicate this dissertation to my lovely mum -Gabriele Schefenacker-Speth- my dad who passed away in 2006 -Dr. Josef Speth-, and my beautiful sister -Isabel Speth- who made me become the person I am.

Valerie Speth, March 2013

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GLOSSARY

Balancing costs: Short-term operational costs a system incurs through output variability and uncertainty.

Capacity costs: Costs associated with the required capacity that enables a system to provide system reliability at any time.

Capacity credit: A credit that expresses the contribution made to system reliability by fluctuating plants that is equivalent to the contribution of conventional thermal plant. The capacity credit is calculated using statistical methods. The estimation of capacity requirements is based on the estimates of the probability distribution of the difference between the available capacity on the system at any point in time and the instantaneous demand. The capacity credit is considered only during the highest peak demand periods.

Capacity factor: The maximum output that can be obtained from a generating source, after planned and unplanned outages. It is expressed as a percentage of total installed capacity. Capacity factors for baseload thermal generators can reach up to 85%. Wind turbines achieve capacity factors of 20% to 40%.

Contribution to peak demand: The contribution to peak demand is defined as the times of 10% highest demand within a year (876 hours).

Environmental costs: Costs that are related to CO_2 emissions or waste disposal.

Levelized cost of energy: Costs per MWh of a payment stream that has the same present value as total generation costs of a plant over its lifetime (including investment, operation and maintenance cost).

Loss-of-load probability: The probability that a load will need to be forced to disconnect from the system due to insufficient generation expressed as the number of years per century in which load shedding will occur.

Penetration level: The share to which wind and solar energy contributes to energy generation expressed as the capacity factor.

Predictability: The predictability of wind and solar power is the difference between the expected and the actual generated energy.

Price-based policy instruments: These instruments provide a stable tariff payment based on a purchase obligation over a defined time period.

Quantity-based policy instruments: This instrument is a legislator mechanisms that provides a fixes price for a certain quantity.

Smoothing effect: Volatile generation units that are spread out in a geographical area compensate each other and result in a less variable generation profile, called the smoothing effect.

System security: The ability of a system to provide energy in times of extreme events.

Variability: The variability is the variance of the power generation from one to the next hour.

Volatility: Volatility is the power difference between two consecutive hours expressed as % of installed capacity.

ABBREVIATIONS

BMU	Bundesministerium für Umwelt
CO_2	Carbon dioxide
CVaR	Conditional Value at Risk
EF	Efficient frontier
e.g.	exempli gratia (for example)
et al.	et alii
EK	Excess kurtosis
EU	European Union
IEA	International Energy Agency
IRR	Internal rate of return
JB	Jarque Bera normality test
K	Kurtosis
LCOE	Levelized cost of energy
NPV	Net present value
O&M	Operation and Maintenance
OTP	Optimal theoretical portfolio
QQ	Quantile-quantile
R&D	Research and development
S	Skewness
UK	United Kingdom
US	United States of America
VaR	Value at Risk
WACC	Weighted average cost of capital

ABSTRACT

Although high investments need to be leveraged to increase the share of wind and solar energy generation, investment risk has not yet been integrated into commonly used approaches of renewable energy scenario development. However, to evaluate and reduce technological risk and associated balancing and capacity costs of increased renewable energy generation, such an integration of risk is a necessary step to take. The dissertation develops an integrated, exploratory research framework to generate optimal wind and solar portfolios under the evaluation of two dimensions: return and risk.

It uses wind and solar generation and forecast data of Germany from three consecutive years (2010 to 2012) and applies mean-variance portfolio theory to construct four optimal wind and solar portfolios. The aim is to create portfolios that either minimize the predictability errors, volatility or levelized cost of energy or maximize the contribution to peak demand for a given level of risk. The methodology aligns the political, the technological and the investor perspective to drive towards political renewable energy goals. Furthermore, it broadens the levelized cost of energy approach by integrating wind and solar balancing and capacity costs.

The results of the analysis show that: (1) a higher share of solar compared to wind energy decreases the risk associated with predictability errors, contribution to peak demand and levelized cost of energy. (2) a portfolio that holds a higher share of wind decreases risk related to volatility. (3) system security costs, here defined as balancing and capacity costs, impede the estimation of long-term levelized cost of energy. (4) using a dataset over several years seems to enhance the reliability of results leveling out high variations of individual years.

This study contributes to renewable energy scenario development by integrating risk, to empirical wind and solar research by analyzing wind and solar distributions in detail, and to the LCOE method by including balancing and capacity costs to the analysis.

The paper has important implications. Policy makers should determine the long-term efficiency of wind and solar portfolios by evaluating return and risk. In order to design efficient support schemes which include technological risk and associates costs, policy should jointly consider technological and investor requirements. Therefore, balancing and capacity should be incorporated to the level of their cost impact on long-term wind and solar portfolios. To create an investor friendly environment which might lead to additional wind and solar investments, policy makers could introduce a feed-in tariff with a component providing incentives for balancing or capacity properties of wind and solar portfolios.

ZUSAMMENFASSUNG

Obwohl große Investitionen getätigt werden müssen, um den Anteil von Wind- und Solarenergie zu erhöhen, schenken erneuerbare Stromversorgungskonzepte dem Thema Investitionsrisiko kaum Beachtung. Durch die Integration der Bewertungsgröße Risiko könnte jedoch technologisches Risiko, hier definiert als Ausgleichs- und Kapazitätskosten, bewertet und reduziert werden. Diese Dissertation entwickelt einen integrativen, explorativen Ansatz zur Bewertung von Wind und Solarportfolien mit Hilfe von zwei Kriterien: Risiko und Ertrag. Diese Dissertation verwendet einen empirischen, deutschen Datensatz, der Erzeugungs- und Prognosedaten für Wind- und Solarenergie dreier, aufeinanderfolgender Jahre beinhaltet (2010 bis 2012). Dies bildet die Grundlage für die Anwendung der Portfolio-Theorie, die basierend auf dem Diversifikationseffekt bei einem gegebenen Risikolevel Portfolien konstruiert, die entweder den Prognosefehler, die Erzeugungsvolatilität, die Energiegestehungskosten minimiert oder den Beitrag in Zeiten der Spitzenlast maximiert. Die Methodik stimmt die politische, die technologische und die Investorensicht aufeinander ab, so dass zukünftig die Energieversorgung maßgeblich durch die tragenden Säulen Wind- und Solarenergie bereitgestellt werden kann. Zudem erweitert sie den Ansatz der Energiegestehungskosten indem sie Ausgleichs- und Kapazitätskosten integriert und dadurch einen Gesamtkostenansatz entwickelt. Die Analyse zeigt dass: (1) ein höherer Solaranteil innerhalb eines Wind- und Solarportfolios das Risiko des Prognosefehlers, der Energiegestehungskosten und des Beitrags zur Spitzenlast minimiert. (2) ein Portfolio mit einem höheren Windanteil Erzeugungsvolatilität minimiert. (3) Ausgleichs- und Kapazitätskosten eine Abschätzung langfristiger Gesamtkosten erschweren. (4) eine Datengrundlage, die sich über mehrere Jahre erstreckt Ausreiser einzelner Jahre glättet und somit die Belastbarkeit der Ergebnisse erhöht. Die Studie leistet einen Beitrag: zur Bewertung von erneuerbarer Energieszenarien, da sie diese durch das Kriterium Risiko erweitert; zu den Erkenntnissen im Bereich Wind- und Solarerzeugung indem sie empirische Datensätze analysiert. Zudem integriert sie Ausgleichs- und Kapazitätskosten in die levelized cost of energy Methode. Die wichtigsten Ergebnisse dieser Arbeit lauten: Eine langfristige politische Effizienzbewertung von Wind- und Solarportfolien sollten durch die Abwägung von Ertrag und Risiko erfolgen. Ein integrierter Ansatz, der Anforderungen aus technologischer und Investorensicht widerspiegelt, könnte somit die Grundlage zur Entwicklung politischer Rahmenbedingungen sein. Hierzu würden Ausgleichs- und Kapazitätskosten in Abhängigkeit ihrer Relevanz in einen Gesamtkostenansatz einfließen. Das Ziel einer erneuerbaren Stromversorgung wird nur erreicht, wenn trotz schwer einschätzbarem, technologischem Risiko, wie beispielsweise Ausgleichs- und Kapazitätskosten, zukünftig weitere Wind- und Solarinvestitionen getätigt werden. Durch regulatorische Rahmenbedingungen könnte dies ermöglicht werden, wie z.B. einem Einspeisetarif, der eine Komponente enthält, die Anreize für hohe Prognosegüte, geringe Erzeugungsvolatilität oder einen hohen Beitrag zur Spitzenlast bietet.

1 Introduction

Green electricity is currently a hot topic. Increasing shares of wind and solar energy in many countries already contribute to a significant degree to the current energy portfolio. Although many countries define goals to drive towards a low carbon energy system, this revolutionary process does not happen overnight. Political frameworks that leverage high investments, secure energy system supply and provide economically feasible solutions are important elements for a successful implementation. Many studies examine wind and solar levelized cost of energy in highly penetrated wind and solar energy systems. However, they neglect the examination of additional risk that might relate to balancing and capacity and ensures short-, mid- and long-term system security. Such risk increases with higher shares of wind and solar energy and is likely to result in system security costs that are not appropriately integrated in current cost approaches.

This dissertation addresses the existing research gap by developing an exploratory integrative concept that outlines the relationship between political, technological and investor risk as well as by discussing a levelized cost of energy approach that includes the risk of system security costs. Since risk diversification within the energy system has a leading role, this publication applies portfolio theory which has recently found many application within the energy sector. Based on wind and solar diversification effects the integrative concept enables the development of ideal wind and solar portfolios that focus not only on costs but also on risk. Of these studies which evaluate German wind and solar generation and forecast data, this dissertation is the first empirical study applying portfolio theory.

1.1. Background and problem statement

A strategic development from a carbon-intense to a low carbon energy system implies a replacement of the existing generation portfolio and requires the interaction of political, technological and investor perspectives to drive towards a common renewable energy goal. Energy policy is one instrument that is able to integrate perspectives. However, policy making is a complex, iterative process that requires learning from previous mistakes (Mitchell & Connor, 2004). In doing so, regulations are able to reflect new market conditions and thus are more likely to be successful. Renewable energy policy aims to reach a specific installation rate of wind and solar energy within a given timeframe. In addition, it needs to keep prices at low levels providing energy to the public as common property (Wait, 2010). The last years showed the success of renewable energy policy, in particular in countries that implemented the feed-in tariff system.

Taking an energy system perspective, not only the political but also the technological perspective that is concerned with energy system security has to be considered.

The current system is designed for nuclear and conventional baseload generators that run at the same level of operation throughout the year. However, wind and solar generators have three characteristics that are very likely to change the operations of the current energy system in the long-term, especially in regards of system security. First, their generation is to a specific degree unpredictable; second, they provide volatile generation; and third, they contribute only to a certain degree in times of peak demand. The following paragraphs discuss the three technological characteristics and derive the impact on the current energy system.

Predictability is defined as the deviation between forecast and actual power generation. It implicates the additional need for short-term balancing (Gross et al., 2006). The phenomenon occurs if an energy plant suddenly shuts up or down due to an unforeseen incident. The accuracy of the forecast assesses the level of required short-term balancing.

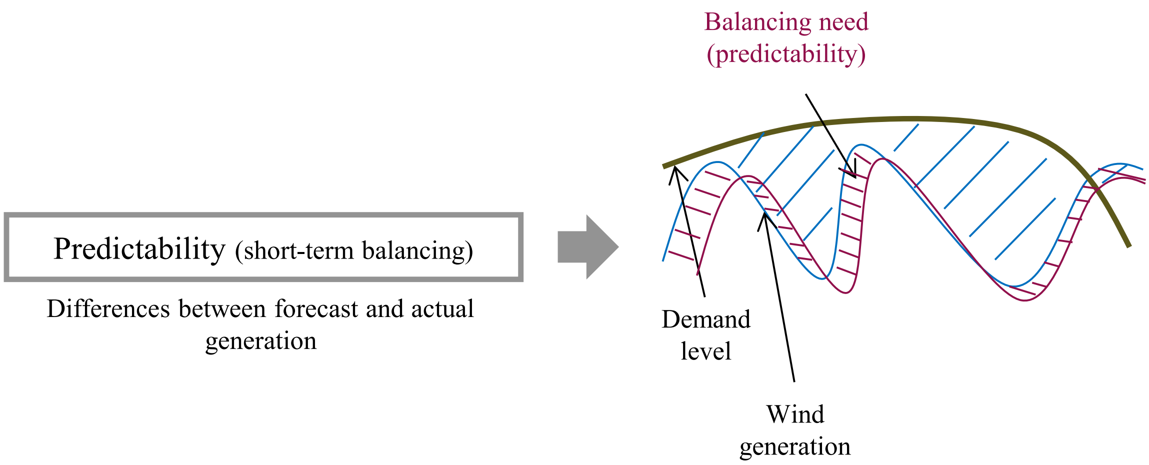

Figure 1: Predictability balancing needs

Wind and solar predictability research is centered around the level of forecast errors occurring in different time periods. Studies outline that the closer the forecast to the actual physical delivery the smaller the forecast error (Weber, 2010). The accuracy of forecast models and the resulting balancing in different timeframes have been mostly researched for wind energy (von Roon & Wagner, 2009). Wind energy forecast improved in the last decade due to advanced forecast software that includes large wind datasets of historical generation and weather data. The 12 to 24 hours day ahead forecast errors for wind still range between 30% to 40% of total production (Holttinen, 2005) which challenges utilities to assign unit commitments to volatile wind or solar generation 12 to 24 hours day ahead. The standard deviation of the forecast error of one single wind farm is 12% , 15%, 15% and 18% for 6, 12, 24 and 36 hours ahead forecast (Carlsson, 2011). Based on the shortage of public available solar forecast and generation data such findings for solar predictability have not been published, so far.

However, some results show that forecasting a large geographical area is more accurate than forecasting one single plant mainly caused by sudden occurring clouds and weather changes (IEA, 2011). Nevertheless, additional forecast error research is needed to determine the impact of the predictability level on short-term balancing. This dissertation uses German hourly day-ahead forecast data.

The second characteristic - volatility - has been managed on the demand side for many years and is a known phenomenon. It is defined as the power difference between two consecutive hours measured relative to the installed capacity. The need of flexible generators that balance the system in the mid-term is determined based on the frequency and the magnitude of volatility (IEA, 2011).

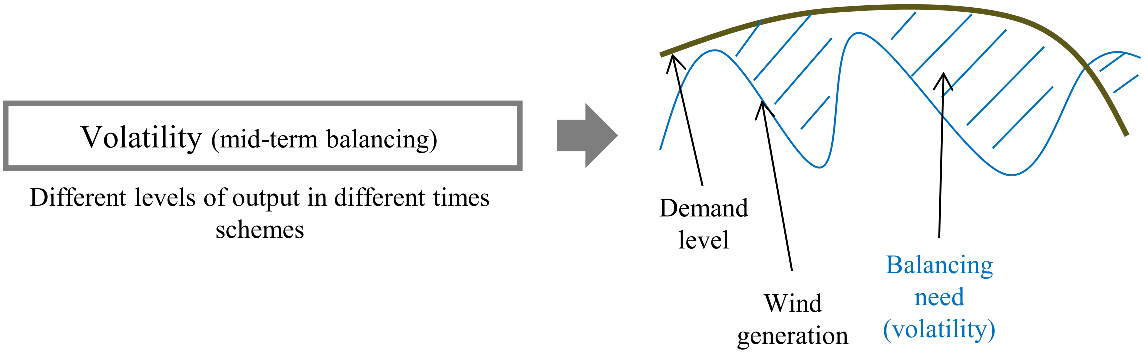

Figure 2: Volatility balancing needs

Introducing wind or solar power to an energy system increases the total volatility of an energy system (NREL, 2011). Former studies focus on wind power generation and optimization approaches to decrease wind volatility by spreading wind farms over a large area creating a smoothing effect (Holttinen, 2005; Roques et al., 2010). They find that less than 30 wind sites in a large area overestimate variability (Holttinen et al., 2011). Only little research on solar volatility has been conducted rooted in the shortage of available generation data. Findings show that the diurnal variability is the highest in June with 140 W/m2 and the lowest in December with 25 W/m2. Furthermore, more sites indicate a lower noon variability, especially in the summer time. The noon variability of one site of 250 W/m^2 falls to 150 W/m^2 for 12 sites in June, for instance (Widen, 2011). Other studies show equal to wind studies that the interconnection of disperse solar plants reduces variability (Mills & Wiser, 2010). To drive towards the goal of a higher renewable energy generation share not only wind but also solar volatility has to be considered (NREL, 2010). Conceptually, the question if a specific wind and solar portfolio minimizes volatility should be raised. The answer of this question is particularly important to determine the need of balancing in the mid-term. This dissertation uses German hourly generation data to determine volatility.

Predictability and volatility require counterparts that balance short- and mid-term variability. As Kirby and Milligan (2009) as well as Katzenstein and Apt (2012) specify, this dissertation defines balancing to occur in the timeframe of seconds to minute, minutes to hours and one day. Generators that provide such short- and mid-term balancing operate very flexible in many hours of the year (Kirby & Milligan, 2009).

Differing from balancing, capacity is defined in timespans of weeks, month and years. Capacity needs relate to system security in the long-term (Gross et al., 2006). Generators that provide capacity operate in very few hours within a year and only in case an energy system is close to a sudden breakdown.

In addition to this, capacity is provided to maintain the certainty that a power generator contributes during peak demand (Crampton & Stoft, 2005). Adding fluctuating generators increases the risk of low contribution, particularly, in times of high demand. Since the reliability of the system decreases with an increasing amount of wind and solar power, additional capacities have to be installed.

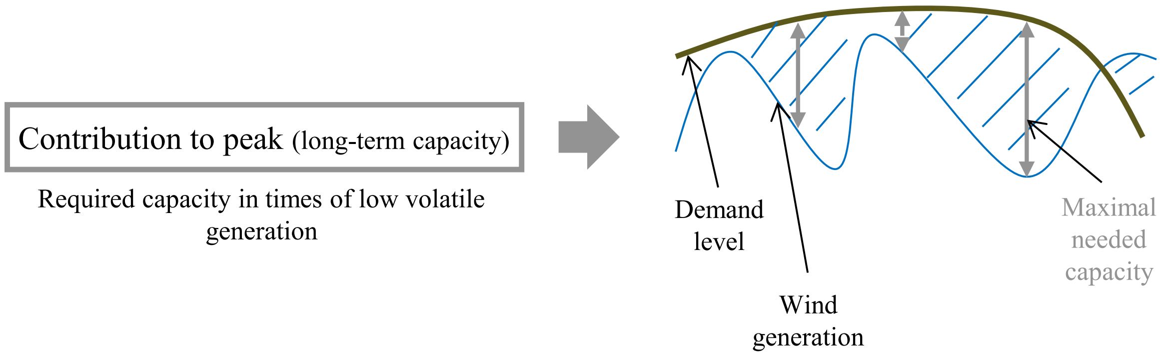

Figure 3: Contribution to peak demand capacity needs

The capacity credit which is the indication to keep the ability of an energy system to perform even in times of insufficient generation has been subject of research for several years (Gross et al., 2006). Various methods to calculate capacity credits for fluctuating power generators have been proposed and used in science (Milborrow, 1996). In general, wind and solar capacity credits are lower than conventional capacity credits and measured in the loss-of-load probability which varies between 6% to 30% highly depending on the degree of wind and solar penetration in the system (Martin & Diesendorf, 1980). Most of the research identified capacity credits for wind and solar within an energy system based on the total fluctuating penetration level. The evaluation of additional capacity needs is essential to determine costs related to system security in extreme situations as well as in times of high demand. This dissertation defines contribution to peak demand as power contribution during the hours within the highest 10% demand.

The degree to which these three technological characteristics can be observed is based on the share between wind and solar energy. Therefore, wind and solar portfolios determine the level of required investments related to balancing (predictability and volatility) and capacity (contribution to peak demand).

The technological perspective of system security influences not only the political cost perspective but might also have an impact on the investor cost perspective since balancing and capacity costs might be passed through to investors. A redesign of policy regulations that might regulate such attempts is very likely to influences investors' behaviour since it may increase or decrease investors' risk and therefore their return expectation.

Most researchers determine investments by the levelized cost of energy which include investment, fuel, fixed and variable operation and maintenance as well as environmental costs (Bode & Groscurth, 2006). Levelized cost of energy is a measure that captures the competitiveness of technologies as well as the per kilowatt-hour cost of building and operating a power plant. This publication acknowledges increasing wind and solar shares and the latest political discussions on balancing and capacity needs that they are very likely to evoke system security costs. Therefore, this thesis introduces two new elements both within the category of system security costs: balancing and capacity costs. Balancing is determined by the degree to which a power plant is flexible to increase or decrease operations in the short- as well as in the mid-term. Capacity is the degree to which power generators contribute to power generation during peak demand in the long-term. These costs become more significant with an increasing share of renewable energies in the system (NREL, 2010) and should be included in integration studies (Skea et al., 2008). The consideration of costs that are related to infrastructure and energy transmission, e.g. grid connection costs lie beyond the scope of this dissertation.

It is surprising that research falls short on fully integrating the technological, political and investor perspectives despite the fact that the relationship of the three perspectives is crucial to determine the success of renewable energy policy making (BDI, 2012). Lately, European policy makers have rather focused on meeting a renewable energy goal than on pursuing an efficient total energy system cost approach (Sachverständigenrat, 2011/2012). This dissertation therefore, develops a wind and solar portfolio approach that integrates all three perspectives to evaluate different wind and solar portfolios on technological and cost risk.

1.2. Theoretical foundation and methodological approach

Portfolio theory is used to identify optimal wind and solar portfolios. In the field of financial securities, questions related to optimal portfolio have been studied for several years (Markowitz, 1952). The theory aims to maximize an expected return for any given level of risk. Risk reduction is attained through diversification that occurs when the return of two or more securities is not perfectly positive correlated.
Within the energy sector, portfolio theory has been mainly used for conventional portfolio applications to calculate optimal investment portfolios in a political perspective maximizing return while minimizing risk (Humphreys & McClain, 1998; Awerbuch, 2000b). Only few approaches integrate wind and solar in their generation portfolio (Awerbuch & Berger, 2003; Jansen et al., 2006; Krey & Zweifel, 2006; Bhattacharya & Kojima, 2010). Other than optimal investment portfolio research, some scientists use the theory for wind deployment maximizing power generation output and minimizing total variability (Drake & Hubacek, 2007) or maximizing contribution to peak demand (Hansen, 2005; Roques et al., 2010), focusing on large area portfolios. These papers analyze generation portfolios from a technological perspective. Thus, previous existing research takes only one perspective – either a technological or political perspective. However, the examination of a generation portfolio from all perspectives, namely from a technological optimizing technological risk and from a political and investor optimizing economical risk seems valuable to successfully drive towards renewable energy goals.

Most portfolio theory research focuses on wind energy although the renewable energy goal comprises solar as well (EREC, 2008). A lack of available solar generation data might be one reason why few approaches integrate solar energy in their portfolio research (Jansen et al., 2006; Krey & Zweifel, 2006; Bhattacharya & Kojima, 2010).

A three-step approach (figure 4) is used to evaluate long-term efficient portfolios from a technological, political and investor perspective. Therefore, this dissertation determines optimized portfolios not only on output but also on risk.

Figure 4: Three-step research methodology

In the first step, a research framework is developed. The empirical evidence about political, technological and investor perspectives on wind and solar development as well as their interactions are examined. Then, the technological risk of wind and solar on system security is outlined before discussing the impact on total energy system costs. The research framework can be used to determine technological optimized portfolios as well as political and investor optimized portfolios including system security costs.

In the second step, prior research using portfolio theory in the energy sector is examined before the research gaps are outlined and the overall approach and strategy is derived.

In the third step, the research framework is applied to the case of Germany. A large empirical German hourly wind and solar generation[1] and 12-hour forecast dataset from 2010 to 2012 is validated by eliminating data errors, excluding unreasonable data values and reconstructing missing data points. The dataset that represents predictability, volatility and the contribution to peak demand is then analyzed in detail discussing probability distributions. Optimal wind and solar portfolios for the technological elements (predictability, volatility, contribution to peak demand) are constructed. Portfolio theory is used to create an efficient frontier for optimized political and investor portfolios maximizing inverse levelized cost of energy. Thereby, levelized cost of energy includes fixed, variable and fixed operation & maintenance, balancing and capacity costs. In the last step, it is discussed if optimized technological portfolios are efficient in regards to total energy system costs.

1.3. Research questions

Diversification as the concept to reduce risk has been matter of research in the financial sector for a long time (Bodie et al., 2011). However, the application in the energy sector has not been intensively discussed, e.g. for wind and solar portfolios. This is surprising, since the integration of different wind and solar technologies in our current energy system and the resulting level of risk and costs gained an increasing public attention in the last years.

Therefore, the aim of this dissertation is to shed more light on technological and total system cost risk related to different wind and solar shares within a portfolio. In the first step, the goal is to identify optimal portfolios from the technological perspective. Thus, the research questions are:

	Wind and solar – technological research questions
Balancing	*What is the ideal wind and solar portfolio that:* • *maximizes predictability* • *minimizes volatility*
Capacity	*What is the ideal wind and solar portfolio that:* • *maximizes contribution to peak demand*

[1] 18.000 wind power plants, 1.1 Mio. solar power plants

In the second step, this thesis calculates optimal political and investor portfolios by minimizing total energy system costs including balancing and capacity costs. The research questions is:

	Wind and solar – political and investor research question
Total system costs	*What is the ideal wind and solar portfolio that:* • *minimizes levelized cost of energy*

Answering the questions above, this research contributes to renewable energy portfolio development by adding the dimension **risk** to the **evaluation**. **By optimizing a total cost approach that integrates balancing and capacity costs** it is conductive to **portfolio theory in the energy sector.** Since there have been only few applications using new optimization elements, the thesis shows manifold ways of the utilization of the theory.

Moreover, the particularities of each element are discussed based on a comprehensive German wind and solar dataset. The dataset represents wind and solar installations spread over a large area in a country that holds a high share of fluctuating energies in the generation portfolio. This extends the **knowledge within the wind and solar research community about wind and solar generation**.
In addition to this, the results contribute to practice by deriving several interesting findings for policy makers and investors. The findings **assist investors** to understand the **risk of additional costs** that might have to be covered by wind or solar power generators in the future. Assessments that are conducted for placing large investments in different generation technologies could use these results to price-in additional risk and provide security for long-term investments.
Furthermore, the thesis offers a different approach of estimating potential changes in energy policy making by examining the interdependency of the fluctuating power generators wind and solar as well as the resulting balancing and capacity needs. **Policy makers** might use these findings to **integrate technological elements such as predictability, volatility and the contribution to peak demand into the development of new policy instruments** that enable the goal to progress towards a low carbon energy system.

1.4. Outline

The dissertation is composed of one introductory section and three main sections. In Chapter 1, the topic is introduced by discussing the background and defining the methodological approach to answer the defined research questions. In Chapter 2, three different perspectives, namely the technological, the political and the investor perspective on a renewable energy goal are discussed. This part closes with the development of the integrated research framework. Chapter 3 discusses portfolio theory and prior applications in the energy sector complemented by the identification of research gaps. Chapter 4 examines based on German data different ideal portfolios that either maximize predictability, minimize volatility or and the contribution to peak demand. An ideal portfolio that minimizes total energy system costs including balancing and capacity costs is calculated, as well. Chapter 5 sums up the previous findings, illustrates the main results and draws conclusions to issue recommendations for policy makers and investors. Figure 5 gives an overview of the research outline.

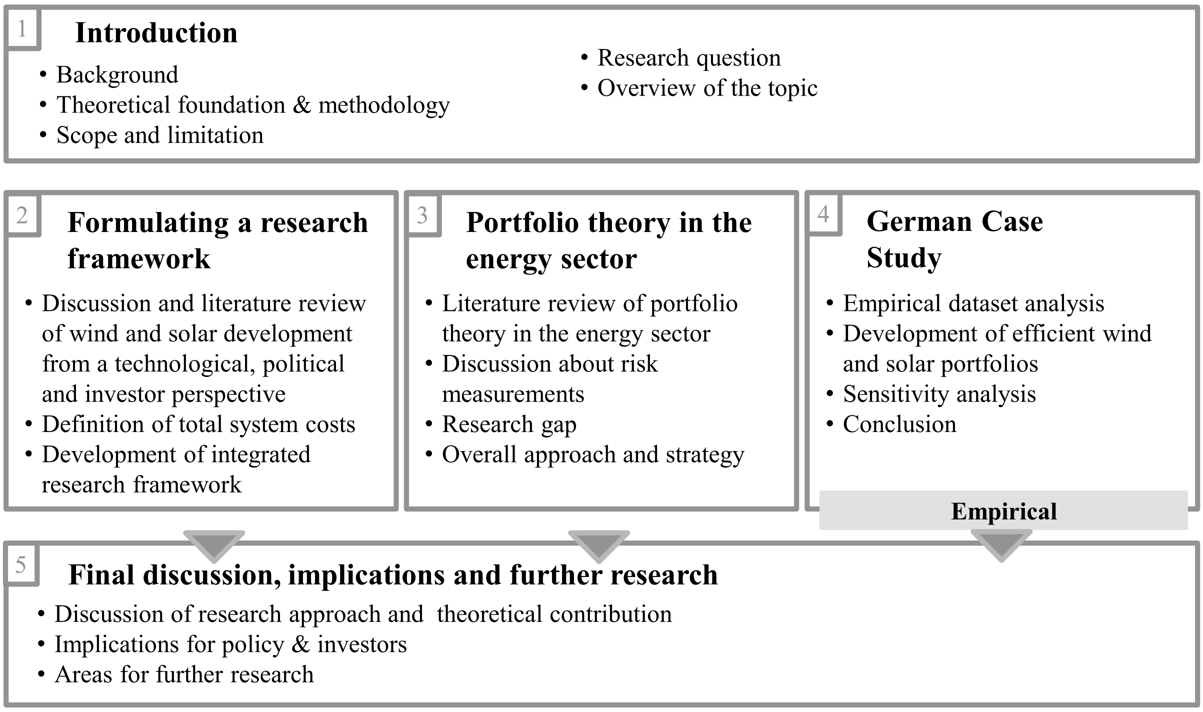

Figure 5: Research outline

2 Formulating a research framework

In the Kyoto Treaty the European Union set the target for European countries to decrease CO_2 emissions by 20% compared to 1990 levels until 2020 (European Commission, 2010a). One essential pillar to meet this target is to switch from a carbon-intense energy generation portfolio which accounted for 38% of the EU emissions in 2007 to a low carbon energy generation portfolio (European Commission, 2010b). Three specific goals are underlining this overall European target.

The first target is *generation risk reduction* in the long-term. The risk of generating power is often associated with the dependency on energy imports. European imports increased in the last years from 40% gross energy consumption in 1980 up to 54% in 2010 (Eurostat, 2012). Another generation risk is the indefinable risk linked to decommissioning and waste disposal, e.g. for nuclear power plants (Greenpeace & BWE, 2012).
The second goal is a *CO_2 emission decrease* to tackle the climate change threat. Several studies have shown that CO_2 emissions rise the global temperature. This unnatural temperature effect is known as global warming and suspected to cause flooding, storms and other environmental disasters (European Parliament, 2006).
The third goal is the *enhancement of cost efficiency*. The limited availability of natural resources caused a steady rise in fossil fuel prices (Eurostat, 2012). This development is very likely to continue which will limit the cost efficiency of power generators that are linked to natural resources. Hence, these technologies will not be the most cost efficient generation technologies in the long-term.
The introduction of renewable energies has taken place in all European countries. Supported by European policy instruments and regulations renewable energies, especially the fluctuating generation technologies wind and solar, have experienced a great development within the last decades. The great renewable energy development of Germany which is now one of the European green energy leaders is outlines in figure 6.

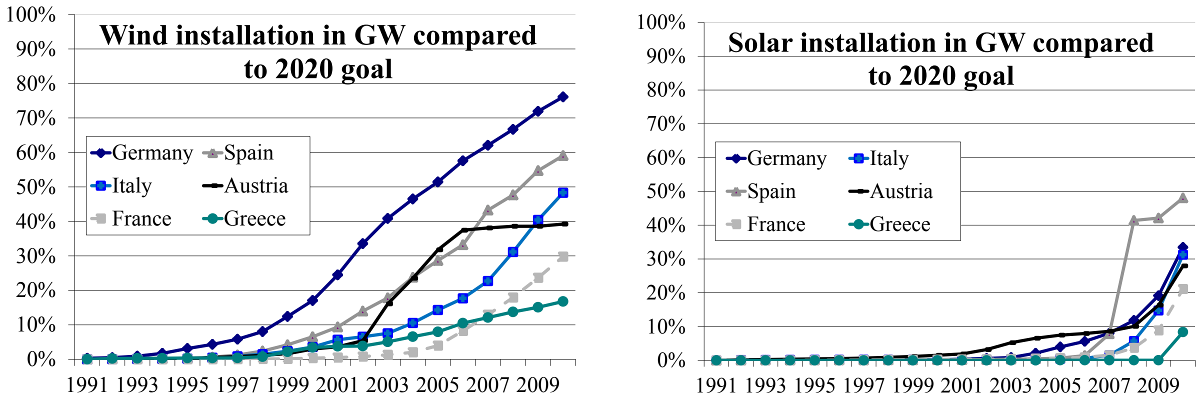

Figure 6: Wind and solar development 1991 to 2010

In 2010, Germany met already 75% of the 2020 wind and 35% of the 2020 solar target. The total renewable energy production in 2010 accounted for 17% of total electricity consumption (BMU, 2012a). Despite high installation rates in the last years, the long-term goal to reach 35% of total electricity consumption by renewable energies in 2030 and 80% in 2050 will require a continuous and persistent wind and solar development (BMU, 2011a). To ensure high annual installation rates and provide an increasing share of renewable electricity the perspectives of different stakeholders towards one renewable energy goal has to be taken into account. This study focuses solely on German wind and solar energy since the potential for other renewable energies such as hydro, bio and geothermal energy are unlikely to contribute to a high degree to the power supply within Germany (Agora Energiewende, 2012). The following sections outline empirical evidence on three perspectives towards renewable energy goals and discuss total system costs before developing the research framework.

2.1. Three perspectives on the renewable energy goal

A review process of literature on three different perspectives establishes the foundation of the research framework. The analysis includes the political, technological as well as investor perspective on wind and solar renewable energy goals in Germany. Publications from the political perspective are conducted by using the German Federal Ministry for the Environment, Nature Conservation and Nuclear Safety homepage. The EBSCO database is used to collect information about the technological and investor perspective, limiting the research to studies that are published in Energy Economy and Energy Policy. The analysis focuses on literature that concerns economic publications excluding engineering-orientated studies. Figure 7 illustrates the three perspectives identified during the review process.

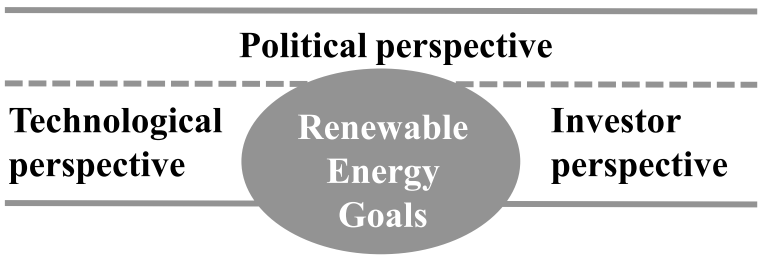

Figure 7: Three perspectives on renewable energy goals

The political perspective of meeting renewable energy goals has been defined by the German government through generating five benefits for society. This development allows society to take responsibility for the future of the children, to limit climate change, to maintain energy security and independence, to create additional growth as well as to increase public participation (BMU, 2012b).

The role of a government within this process is to enable a continuous progress towards setting objectives, for instance, by implementing market policy instruments either price-based e.g. the feed-in tariff system or quantity-based, e.g. the quota system. The design of policy instruments determines return and therefore risk associated with wind and solar investments (IEA, 2011). Hence, the foundation for a successful wind and solar deployment are wisely designed policy regulations. In the German market, the introduction of a price based feed-in tariff system for wind and solar energy shows that this support scheme enables a continuous rise of wind and solar power as shown in figure 8 and 9.

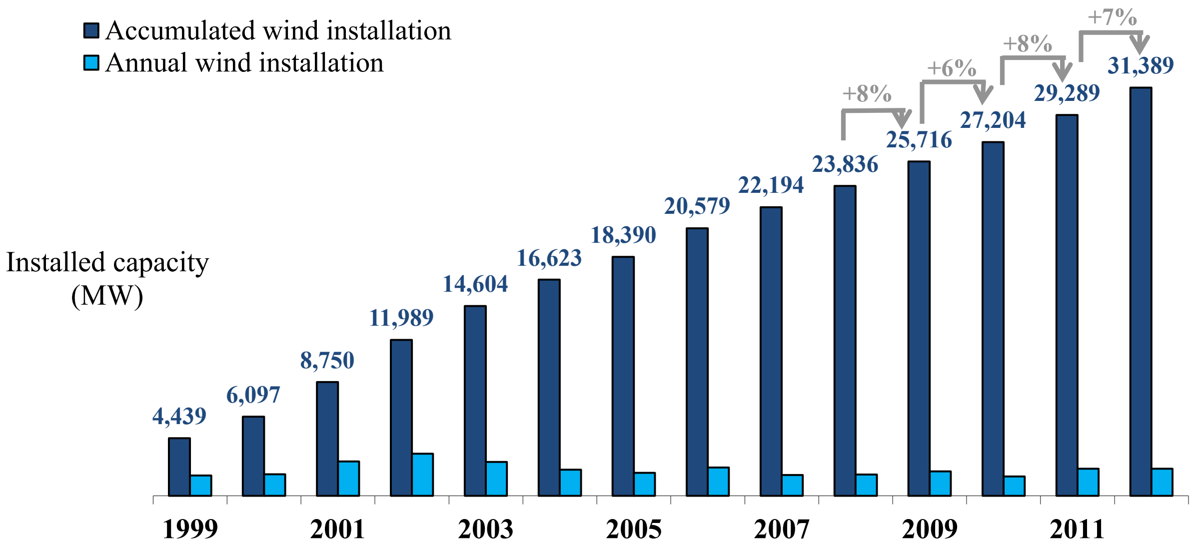

Figure 8: German wind development 1999 to 2012

Source: Eurostat 2012/BMU 2012a

The German wind development is relatively stable from 1999 to 2012. In the first four years after the introduction of the German renewable energy law in 1999, the installation rates increased up to 3,2 GW in 2002. Since 2004 the annual rates vary between 2.0 GW and 1.5 GW.

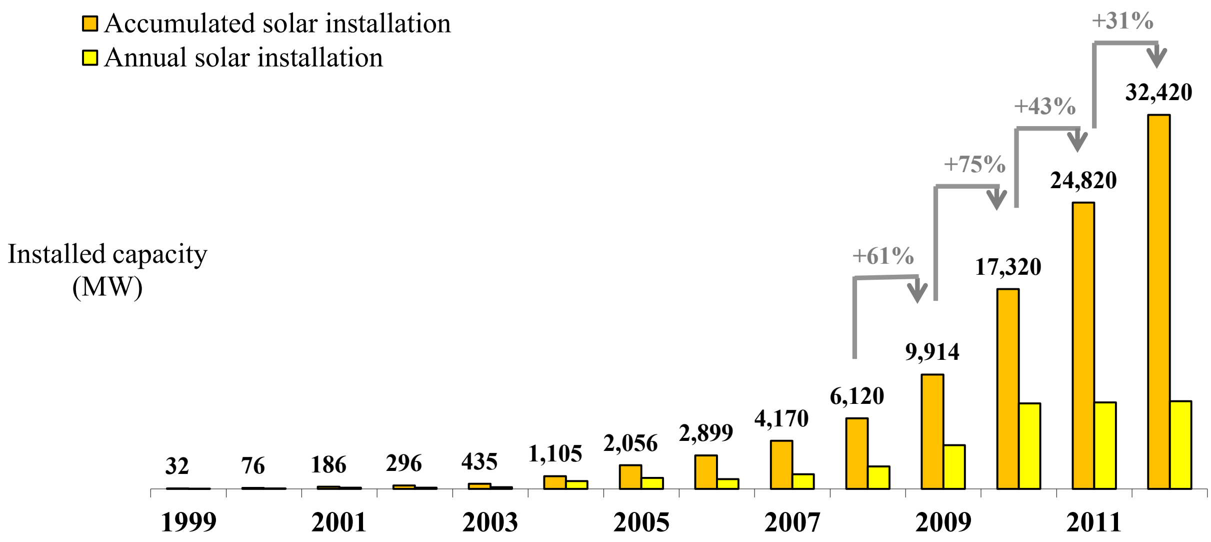

Figure 9: German solar generation 1999 to 2012

Source: Eurostat 2012/BMU 2012a

Solar deployment started in 2004 with annual installation rates of about 1 GW until 2007. Extreme high installation is identified between 2009 and 2012 with annual rates of 7.5 GW. In 2012, the total German installed solar power exceeds the wind power installation for the first time.

Installation rates are positive correlated to renewable energy allocation fees which has led to additional costs for green energy in Germany in the last years. By 2011, these additional costs for wind onshore reached 2.58 Mio. Euro, for solar 6.9 Mio. Euro, respectively (BDEW, 2011). The discussion about an increasing additional financial burden passed on to end consumers has lately elicited much debate. Thus, the German government adjusted in 2011 and 2012 the renewable energy law by decreasing the feed-in tariff and limiting additional installations (Altmaier, 2012).

As outlined, the goal of the political perspective is double sided. On the one hand, it aims to create an ideal political framework to accelerate wind and solar installations. On the other hand, it seeks to limit the risk of additional costs that are linked to high wind and solar installation rates. Therefore, politicians should drive towards balancing this dichotomy and start to evaluate generation portfolios more on a long-term perspective including risk. This might enable them to develop support schemes that allow financing new technologies today in order to gain a long-term benefit in the future. The question that is pursuit by the political perspective is *"What is the ideal wind and solar portfolio that minimizes levelized cost of energy."*
At the early days of wind and solar generation, the technological perspective of achieving renewable energy goals mainly focused on decreasing generation costs (Barbose et al., 2011).

A rapid technology development provoked by high R&D investments accelerated falling generation costs. In the last years, the technological perspective shifted from topics related to generation costs towards topics relevant to system security.
System security can be associated with transmission lines (DENA, 2005), the flexibility of an energy system (IEA, 2011) and reliability during peak demand (Oren, 2003). An increasing amount of power plants require strong transmission lines that are able to handle additional power generation. Although functioning transmission lines and associated costs lately attracted notice, this dissertation excludes costs associated with transmission and focuses on flexibility and reliability during peak demand, only.

The discussion about flexibility within an energy system has recently started. Flexibility is required if electricity generation varies from the predicted energy amount or if generators produce different amounts of energy in consecutive hours (IEA, 2011). Even though, there are still enough generators that are able to balance fluctuating generation in the short- or mid-term either caused by low predictability or high volatility, there might be a shortage of flexible generators in the next decades (Skea et al., 2008).

Based on empirical data, figure 10 shows that the times in which wind and solar energy were correctly predicted varied for solar as well as for wind forecast in the observed years (2010 to 2012). Nevertheless, in 28.7% of 8,760 hours solar power and in 44.3% of 8,760 hours wind power required additional system flexibility to balance short-term variation in 2012.

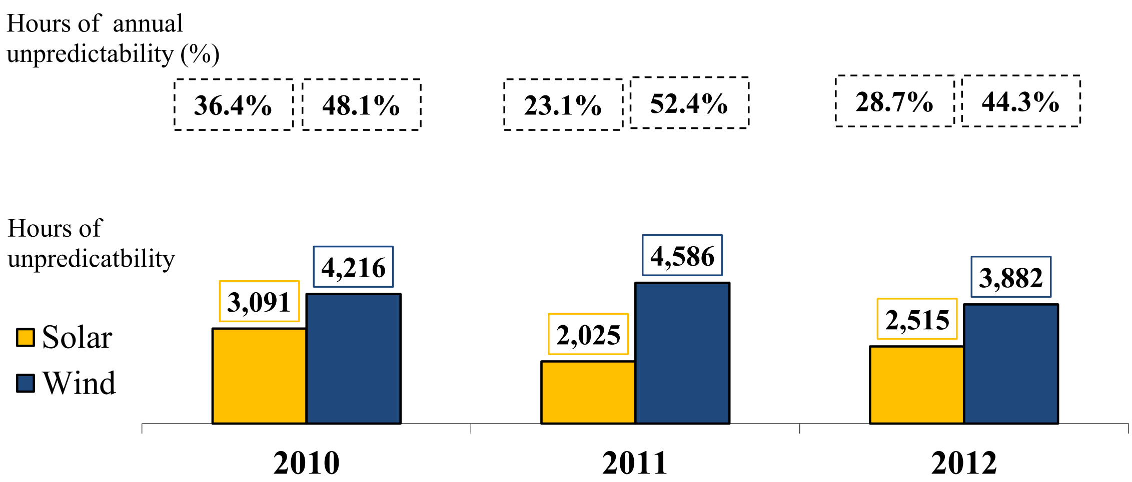

Figure 10: German unpredictable wind and solar generation 2010 to 2012

Source: EEX Transparency platform

In addition to the required flexibility within these hours of low predictability, mid-term balancing caused by volatility was needed. Figure 11 outlines that the hours of volatile solar generation increased from 2010 to 2012 from 3,261 to 3,808 and from 4,364 to 4,373 for wind power generation. In these times, additional system flexibility for mid-term balancing was required.

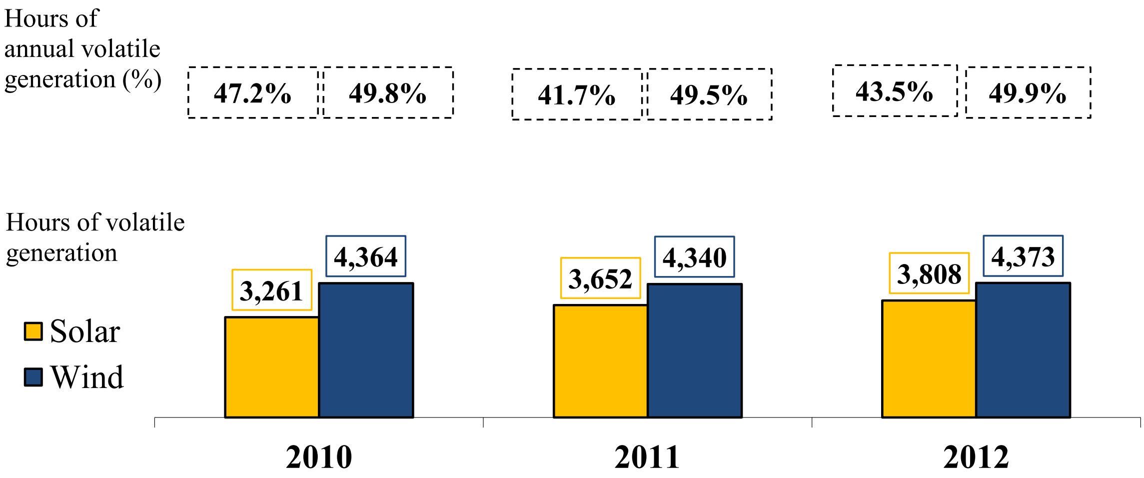

Figure 11: German volatile wind and solar generation 2010 to 2012

Source: EEX Transparency Platform

Not only the risk of additional balancing caused by low predictability and high volatility but also the requirement of providing reliability during peak demand has been discussed, recently. The current overcapacity of generators is likely to decrease since conventional and nuclear power plants retire in the next years. This leads to higher risk that the energy system is unable to provide capacity during peak demand.
Solar contributed in the range of 42% to 64% hours of peak demand compared to wind ranging from 99.5% to 97.6% hours (figure 12a). The contribution to peak demand is defined as the certainty a generator contributes for a known percentage. Figure 12b outlines the percentage in kilowatt-hours of wind and solar energy contribution to system security during the highest 10% peak demand from 2010 to 2012. The very low contribution in 2010 of solar might be matter to missing data or to a lower solar radiation year compared to average. Another reason might be a more disperse located solar portfolio in 2011 and 2012. The kilowatt-hours that wind and solar energy contributed to peak demand increased from 8.8% in 2010 to 12.3% in 2012. The remaining 88.7% in 2012 were generated by non-renewable energy generators. This said, it is clear that the certainty that wind or solar contribute for a known percentage to peak demand is low. The contribution varies from year to year and is related to weather conditions that are difficult to predict for long time horizons.

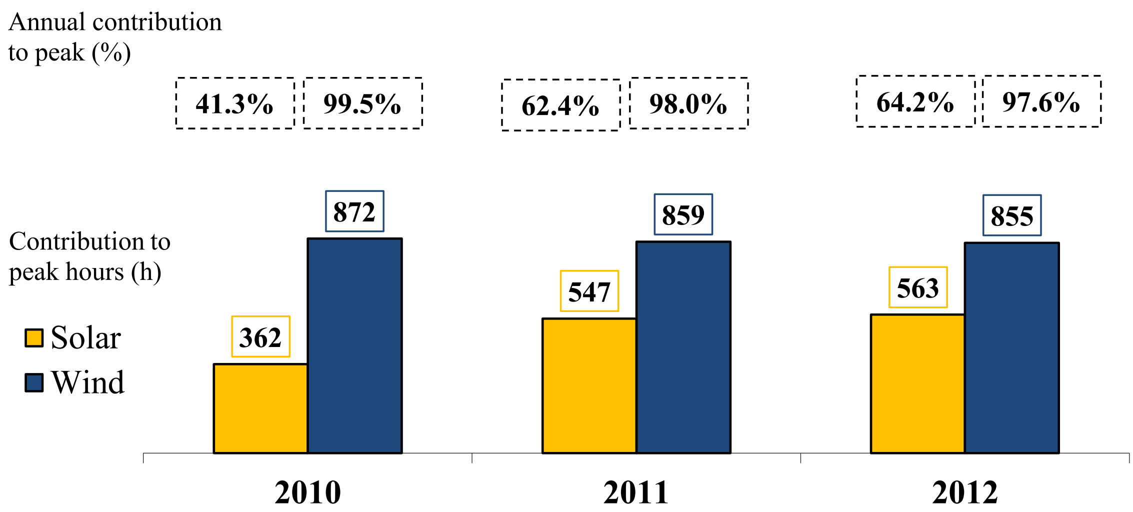

Figure 12a): German wind and solar capacity contribution to peak demand 2010 to 2012

Source: EEX Transparency platform / Measure: in hours

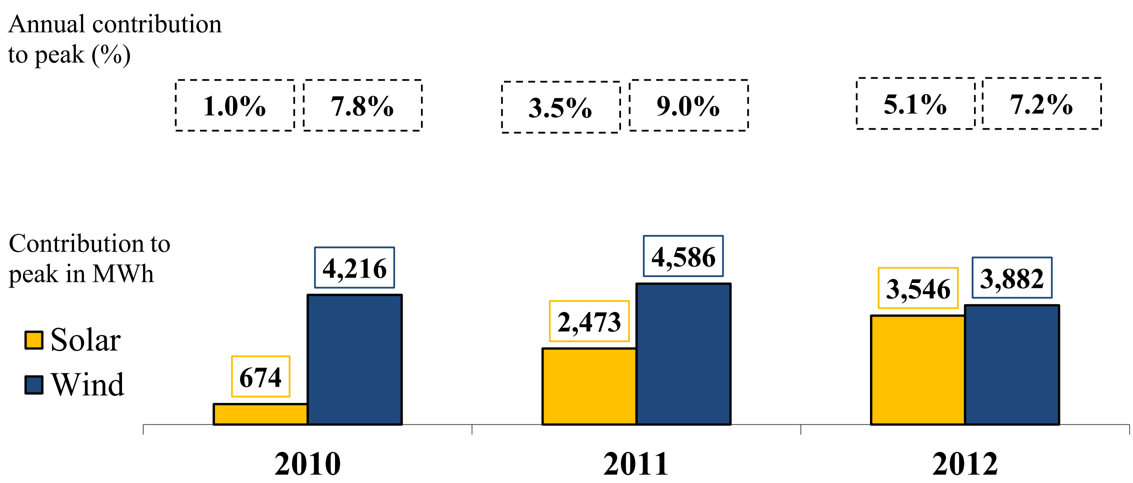

Figure 12b): German wind and solar capacity contribution to peak demand 2010 to 2011

Source: EEX Transparency platform / Measure in MWh

As discussed before, the challenge to cope with additional short- and mid-term flexibility as well as reliability during peak demand rises with an increasing share of fluctuating generators. The question that is pursued by the technological perspective is *"What is the ideal wind and solar portfolio that maximizes predictability, minimizes volatility and maximizes contribution to peak demand."*

The investor perspective is embossed by investors that place wind and solar investments is Germany. For several years, the feed-in tariff system offered good returns for limited risk which attracted many investors (Lüthi & Wüstenhagen, 2008).

Unplanned adjustments of regulations, e.g. in 2010 might have changed the relation between return and risk. Therefore, it is questionable if the investor of yesterday will be the investor of tomorrow. Previous investor groups might either focus on industries with higher return options or on less risky investments. To prevent a lack of investments, new investor groups might have to be identified. As outlined in figure 13 investments increased during the stable regulatory feed-in tariff system framework but decreased in times of regulatory adjustments between 2010 and 2011.

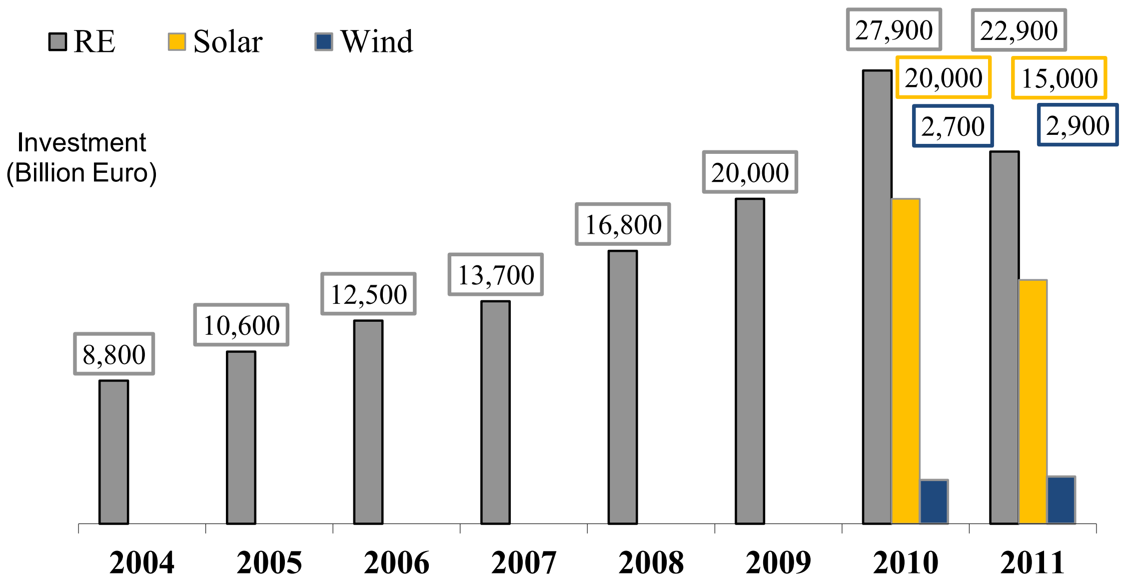

Figure 13: German renewable energy investments 2004 to 2011

Source: BMU 2011b

The analysis of the investor perspective indicates that leveraging high investments might be related to the design and reliability of a political regulatory framework. This goes in line with findings of other scientists (Bürer & Wüstenhagen, 2009). It is assumed that any regulatory adjustment, e.g. regulating who is responsible for additional balancing and capacity costs might influence an investor's decision because it influences return and risk. Thus, investors should include technological risk in their evaluation approaches since it might lead to additional costs. The investor perspective should go align with the political perspective asking the research question: *"What is the ideal wind and solar portfolio that minimizes levelized cost of energy"*.

Ultimately, we can be sure that a long-term shift from a carbon-intense to a low carbon energy generation portfolio will be executed mainly based on the alignment of the political direction. At the same time, the progress toward such a goal will only be successful if all stakeholders are taken into account. Therefore, it is crucial that renewable energy deployment policies are designed within a technological and investor perspective in mind. So far, the three perspectives have been treated as distinct research areas but the interaction between them has not been noticed yet. Figure 14 summarizes the relationship between the perspectives which are discussed in the upcoming paragraphs.

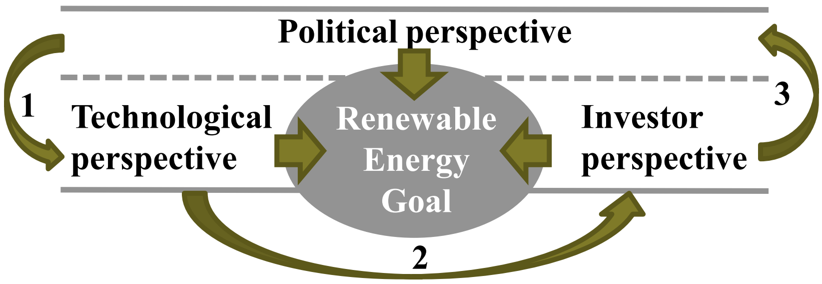

Figure 14: Interaction framework of political, technological and investor perspective

First, the interchange between the political and the technological perspective is important in the way that policy instruments close the financial gap between the costs of new technologies and the market price. To construct instruments that serve as a catalyst to facilitate a large-scale commercialization of wind and solar energy (Mormann, 2012) politicians need to be aware of actual generation costs. Policy instruments define technological requirements that have to be met to receive financial support (e.g. feed-in tariff, tax credit). As an example, wind generators have to be technologically controlled by third parties if they want to be eligible to receive the feed-in tariff. The detailed knowledge about a technology and the associated technological risk is therefore crucial to design successful political frameworks (Klessmann, 2012).

Second, the intensity of the relationship between the technological and the investor perspective determines the risk assessment of a technology. Technologies are difficult to evaluate for investors, especially if they are newly introduced to the market. A comprehensive technological understanding attracts a wider range of investors increasing the potential of available capital that can be leveraged. To provoke the same amount of investments despite higher technology risk investors commonly request higher return opportunities (van Giessel & van der Veen, 2004). Therefore, the key is to increase competition by limiting technological risk. This drives down financing costs, activates a large group of investors and consequently leads to a large community that supports wind and solar deployment.

Third, the investor perspective determines how fast a renewable energy goal can be reached. A successful shift towards a low carbon energy system depends on the ability to leverage investments not only from one but from several investor groups. Policy instruments that provide high return levels compared to the given level of risk attract investors. The success of the feed-in tariff system (price-based policy instrument) which ensures a predetermined fixed profit for power generation for a timeframe of twenty years, highlight the relatively low risk assumption of such a policy instrument (Lüthi & Wüstenhagen, 2008). Vice versa, quantity-based policy instruments that offer less secured returns might result in a shortage of investments. Instruments that only partly regulate risk tend to limit investment opportunities to specific investor groups that are able to overcome price, volume and balancing risk (Mitchell & Connor, 2004). Surprisingly, an integrated concept that embraces all perspectives has not been developed. There might be several reasons. First, the relatively low share of wind and solar (10% to 15%) until just lately resulted in little technological risk. The required balancing and capacity needs caused by wind and solar energy were provided by the overcapacities within most of the current energy systems (Hiroux & Saguan, 2010). Second, most countries have experienced an excess supply of investors in the last decades (BMU, 2011b). One reason might have been the design of policy instruments that limited technological risk and enabled different investor groups to place high investments in wind and solar power. Despite increasing shares of wind and solar generation in many European countries, supply security has received some attention just recently. It is compelling that some authors argue that balancing and capacity costs will attract more notice with an increasing amount of wind and solar energy (Skea et al., 2008). Unregulated risk which might cover additional system balancing or capacity costs is likely to jeopardize the placement of future wind and solar investments (Mormann, 2012).

The empirical literature review of the three perspectives and their interaction towards renewable energy goals is the foundation for the research framework of this dissertation. First, the political aim to attract high investments to accelerate the shift from a carbon-intense to a low carbon electricity generation at moderate costs is accepted. Second, the research shows that the political perspective is closely linked to the investor perspective. Therefore, achieving renewable energy goals is assumed to be sensitive to successful policy instruments that integrate all perspectives and enable an efficient renewable energy portfolio in the long-term. Third, since potential technological challenges increase, especially in a highly penetrated wind and solar generation portfolio, this dissertation acknowledges that resulting costs should be integrated in a research framework. This study shifts the view of single stakeholder towards the view of a country-level perspective and responds to the call of politicians to change the generation portfolio towards wind and solar power at moderate costs (BMU, 2009), the call to identify technological challenges related to balancing supply and demand (Lund, 2006) as well as investors' requests of a stable investment environment (Held et al., 2006).

2.2. Total energy system costs for wind and solar

Generation portfolio research mainly focuses on levelized cost of energy (LCOE) of different technologies including investment, fuel, fixed and variable operations and maintenance costs. Some studies that examine portfolios holding conventional, nuclear and renewable generators broaden the original approach and add environmental costs either defined as carbon emissions (Jansen et al., 2006; Roques et al., 2006; Bhattacharya & Kojima, 2010) or waste (Krey & Zweifel, 2006) to their levelized cost of energy approaches (discussed in detail in Chapter 3). By integrating environmental costs, the costs of conventional and nuclear electricity generation increase.

Although wind and solar generation do not cause environmental costs, it should be recognized that additional balancing and capacity costs might occur. The level of predictability, volatility and contribution to peak demand are elements associated with additional system security costs. Therefore, this dissertation proposes to introduce two additional cost elements to the levelized cost of energy approach: balancing and capacity costs.

Differing from prior research this dissertation focuses on the optimal share between wind and solar energy only and excludes a cost analysis for conventional and nuclear generators. Figure 15 integrates the three technological elements in the framework, reflects the resulting balancing and capacity costs and shows their impact on total energy system costs.

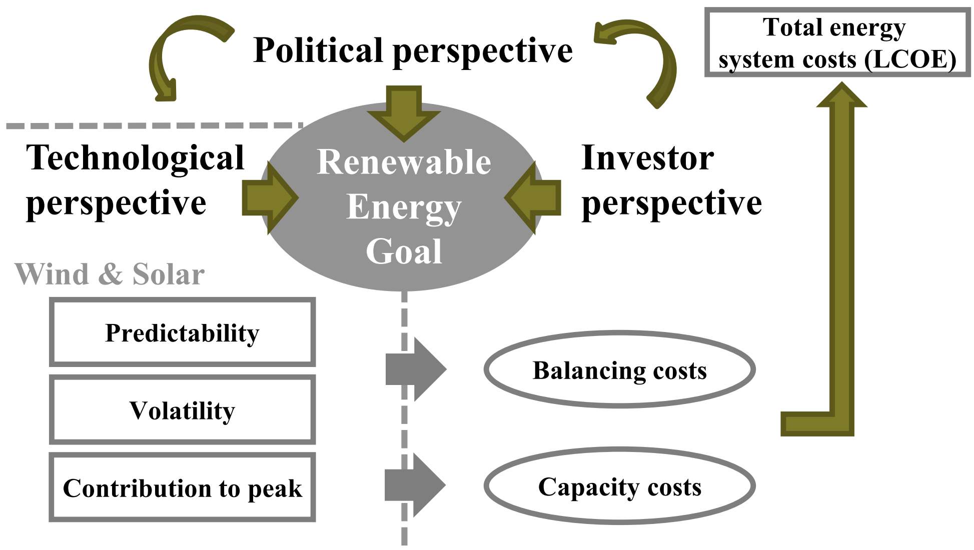

Figure 15: Integrated research framework

Additional technological risk caused by predictability, volatility and the contribution to peak demand lead to balancing or capacity costs that diminish investors' return conditions. Thus, investors either price in a higher risk premium which increases financing costs or even decide to withdraw their investment. Both reactions are contrary to achieve renewable energy goals. The integration of balancing and capacity costs into the political perspective enables governments to capture additional risk and establish an investor friendly environment that includes technological risk. The total energy system costs can be evaluated by determining the balancing and capacity costs of different wind and solar portfolios.

The research framework is used to perform portfolio theory and develop three ideal technological portfolios optimizing for predictability, volatility and contribution to peak demand. Then, balancing and capacity costs are integrated into levelized cost of wind and solar energy before calculating an ideal political and investor portfolio that optimizes levelized cost of energy.

3 Portfolio theory in the energy sector

Portfolio theory has been originally developed for financial securities to create portfolios which maximize the expected return for a given level of risk or minimize risk for a given level of return (Markowitz, 1952). In the past, it has found some applications in the energy planning sector to minimize society's energy price risk (Bar-Lev & Katz, 1976; Humphreys & McClain, 1998). The literature review is conducted using the science direct database in early 2011 searching for portfolio theory within the renewable energy sector (synonyms wind, solar, renewables). In addition to this, databases of German Universities that focus on portfolio theory have been researched. A total of 2,175 articles are found of which only 12 integrated either wind or solar energy generation in their portfolio approach. From a return perspective, the analysis identifies four main research streams: levelized cost of energy, net present value, energy output per installed capacity and internal rate of return. The following review of existing literature seeks to evaluate the approach of using portfolio theory to develop optimized wind and solar portfolios.

Portfolio Theory – Research streams

- **Levelized cost of energy (LCOE)**
- **Net present value (NPV)**
- **Energy output (kWh/installed capacity)**
- **Internal rate of return (IRR)**

Figure 16: Portfolio theory research streams

3.1. Literature review

3.1.1. Levelized cost of energy research stream

The application of portfolio theory to determine ideal generation portfolios has been first used by Bar-Lev and Katz (1976). They evaluate the associated risk of generation portfolios of different utilities. Their regional approach shows that these portfolios are diversified, however characterized by high return and risk which is a result of a regulatory regime that encourages risk seeking. Humphreys and McClain (1998) use portfolio theory to evaluate the US generation mix including the generation technologies oil, natural gas, coal, and nuclear power. Returns are defined as British Thermal Units per dollar. Risk is defined as the standard deviation of normally distributed returns. Their approach aims to offset price volatility in the long-term and shows that with the inclusion of expected externality costs, natural gas would be favoured for the shift away from oil. Both studies contribute to the application of portfolio theory in a liberalised electricity market.

The first study that includes renewable energy generation in their portfolio approach is published by Awerbuch and Berger (2003). They use portfolio theory to evaluate two EU energy portfolios, one in 2000 and a second in 2010, to answer the question if these generation portfolios are cost efficient. Returns are defined as the holding period returns measured as the inverted levelized total costs in kWh/UScent. The levelized cost include fixed investment, fuel, variable and fixed operation & maintenance (O&M) costs. Risk is defined as the standard deviation of the return variance. Awerbuch and Berger (2003) evaluate in the first step a portfolio of oil, gas, coal and nuclear power. Next, they add wind generation to the portfolio and find wind to limit fuel price risk. A sensitivity analysis shows that wind within the portfolio decrease portfolio risk. However, the results are highly sensitive to the levelized cost of energy. This publication contributes in two ways. It is the first approach that defines returns by technology specific unit costs (Jansen et al., 2006) instead of using the weighted average cost of capital (WACC). This procedure is based on the argument that the WACC does not result in good decision making for placing investments (Awerbuch, 2000a). Second, it is the first publication that includes renewable energies in a generation portfolio based on the argument that wind reduces overall risk even though stand-alone costs are higher (Awerbuch, 2000b).

Jansen et al. (2006) apply portfolio theory to evaluate the efficiency of the Dutch power generation mix in 2030. The aim of this study is to gain further insights on the impact of CO_2 price variation, gas prices, and biomass prices on the cost efficiency of a generation portfolio. The scientists analyze a portfolio that include gas CHP, coal, nuclear, wind offshore, wind onshore, solar, hydro, biogas and biomass. Returns are defined as levelized cost of energy measured in Euro/MWh including investment, fuel, variable and fixed O&M costs. They extend the approach of Awerbuch and Berger (2003) by adding environmental costs defined as CO_2 costs. They assume normally distributed returns, risk is measured by the standard deviation. In the first step, the researchers calculate a scenario with low, in the second step a scenario with high renewable energy penetration before performing a sensitivity analysis. The results show from a social-economic perspective that risk could be robust and significantly reduced by renewable energies through diversification. Furthermore, they find that the economics of renewables are highly sensitive to gas prices. This research contributes by adding environmental costs to the total levelized cost of energy approach.

Krey and Zweifel (2006) determine efficient frontiers for Switzerland and the US and evaluate the technology mix in 2003. The Swiss generation mix include conventional thermic, storage hydro, run of river, nuclear and solar power differing from the US generation portfolio holding oil, gas, coal, nuclear, hydro, bio and wind energy. Returns are defined as expected levelized cost of energy expressed as percentage of cost savings including investment, fuel, operations as well as nuclear decommissioning waste disposal costs. The approach assumes normally distributed returns and defines risk as the standard deviation. After performing cost efficient portfolios for Switzerland and the US, they find that in none of the countries an efficient combination of generating technologies is implemented. They conclude that the expected returns are too low for the given risk. The main contribution of this paper is the integration of costs that are associated with nuclear power generation.

Bhattacharya and Kojima (2010) use portfolio theory to calculate ideal cost efficient portfolios within the Japanese market including wind and solar generation. Their portfolio exists of oil, lignite, coal, nuclear, hydro, wind, solar and biomass. Returns are defined as the levelized cost in MWh/dollar consisting of investment, fuel, O&M as well as environmental costs (defined as CO_2 costs). Risk is defined as the standard deviation. After creating the efficient frontier based on the assigned costs per technology the scientists perform three sensitivity analysis. Varying fossil fuel prices, renewable investment costs and international carbon prices show that the price fluctuation and not the absolute price figures are the cause of high investment risk. An international carbon price has a negligible effect on renewable energies and therefore does not decrease the renewable energy portfolio risk. Furthermore, they calculate that 9% renewable energy penetration would result in a moderate rise of costs but in a high decrease of risk. The study contributes by providing interesting findings on the impact of sensitivities on efficient portfolios.

Delarue et al. (2011) show the influence of additional wind integration costs on total system costs by applying portfolio theory to the Belgian market. The generation portfolio includes oil, gas, coal, nuclear and wind energy. Returns are defined as costs per produced energy unit in Euro/MWh including in the first scenario investment, fuel, fixed and variable O&M costs. In the second scenario additional risk that is associated with a lower capacity factor of wind is added to investment and fixed O&M costs. Risk is defined in both scenarios as the standard deviation. The results of the first calculation confirm former approaches. Implementing wind reduces total risk. However, the second calculation outlines the need and relevance of distinguishing between fixed and variable costs within a portfolio. It points out that system integration costs are relevant. Taking into account risk, which is defined as opportunity costs of a lower wind capacity factor limits the value of wind generation. This is the first publication that integrated costs associated with non-dispatchable variable power sources. The scientists show that further research might include risk associated with predictability. As discussed above, the first research stream minimizes levelized cost of energy for a generation portfolio including conventional as well as renewable energy generators.

3.1.2. Net present value research stream

The second research stream is introduced by Roques et al. (2006). They argue that generation technologies cannot be judged by their generation costs but rather by the expected return and risk, whereas risk should include electricity price, CO_2 and fuel price risk. In their study, they use UK data to generate a portfolio of natural gas combustion, coal and nuclear generators. They include investment, fuel, variable and fixed operations & maintenance as well as nuclear waste costs and define returns as net present values of an investment. Risk is measured by the standard deviation. The results show that electricity prices, CO_2 and fuel prices are positive correlated and determine the usage of combined-cycle gas turbines. The contribution of this research is the introduction of a new return measurement defined as net present value. This publication questions if the market is able to provide incentives that result in the most cost efficient generation portfolio in the long-term including all energy costs.

The first and the second research stream define different returns but use the assumption that risk is fully represented by mean and standard deviation. The third research stream is consistent with this assumption but follows the concept of diversification caused by disperse located wind farms. In these studies, returns are measured as energy output instead.

3.1.3. Energy output per installed capacity research stream

Hansen (2005) applies portfolio theory to the case of North Carolina to evaluate the contribution of disperse located wind farms on providing energy at peak demand. He looks at the generation of three wind farms individually and defines return as the capacity factor during peak hours. Based on the assumption of a normal distribution, he defines risk as the standard deviation. He evaluates the capacity factor in different seasons and finds that the ideal portfolio differs in each seasons. His results show that utilities need to decide in which peak period the capacity is more valuable. Furthermore, he outlines that his research falls short on providing insights of the confidential level of occurrence and the usage of data that exceeds the time period of one year. The research contributes to energy planning in terms of reducing volatility in hours of peak demand.

Drake and Hubacek (2007) use portfolio theory to understand the impact of area widespread wind generators on volatility in the UK. They analyze four different wind locations and define returns as the total generated energy per installed wind capacity. The analysis assumes a normal distribution and defines risk as the standard deviation. In the first step, they create four different generation curves based on wind speed data. In the next step, they calculate efficient frontiers for four wind farms that maximize output per unit and minimize variability. Their results show that variability can be reduced by a given widespread dispersion of wind farm sites.

Furthermore, they outline that wind and solar power complement each other over the year but their relationship on an hourly basis is difficult to tell. This research contributes to energy planning by describing the risk reduction effect caused by lower variability of wind farms located in different areas.

Roques et al. (2010) apply portfolio theory to evaluate the most efficient European wind portfolio in terms of energy output and contribution to peak demand. The analysis is based on wind generators located in Spain, Germany, Austria, Denmark and France. Two scenarios - one with and one without national wind resource potential and transmission constraints - are built to compare the efficiency of projected portfolios in 2020 to the efficient frontier. Returns are defined as total output per installed wind capacity. In the first scenario, all hours of the year are examined. In the second step, only the 10% of hours that contribute to peak demand are included. The approach assumes a normal distribution and defines risk as the standard deviation. The results show that transmission grid constraints limit the potential diversification gains. This study contributes to portfolio theory by including different countries and by evaluating the diversification effect during peak hours decreasing variability.

Rombauts et al. (2011) perform portfolio theory to shed more light on efficient wind portfolios including transmission constraints. The analysis considers seven wind locations in the Netherlands. Returns are defined as wind output per installed wind capacity. Risk is defined as standard deviation. In the first step, the scientists calculate the ideal portfolio without transmission constraints. In the second step, they construct an efficient wind portfolio defining risk as the hourly wind power differences after transmission. The results state that the lack of cross border transmission capacity determine the diversification effect that is generated by installing wind generators in different locations. In addition to this, the findings show that transmission capacity plays an important role in reducing risk of a variable wind power profile.

As outlined above, the third research stream contributes especially to energy planning under the assumption of returns being normally distributed. The fourth research stream differs from this assumption and introduces another measurement to capture risk.

3.1.4. Internal rate of return research stream

Borchert and Schemm (2007) utilize the fourth research stream and evaluate risk in their portfolio theory application in the Dutch market. Their research approach estimates risk that can be associated with investing in off-shore wind plants versus the risk investing in on-shore wind plants. Returns are defined as the internal rate of return defined as the discounted net present values of investment, fuel, fixed and variable O&M costs (as percentage of invested capital). Risk is measured by the Conditional Value at Risk (CVaR) at a confidence level of 0.95 using a Weibull distribution. The analysis uses data of 14 different on- and off-shore wind locations and rebuilds in the first step generation curves based on wind speed data. They find that if a feed-in tariff system is in place good wind onshore locations are more beneficial to invest in. Furthermore, the investment becomes even less risky by spreading it over different located wind onshore plants. The approach introduces a new measurement to evaluate risk within renewable energy portfolio theory. It calculates an efficient frontier of ideal investments by maximizing returns while meeting the CVaR lower than the maximal level of loss expectations. The study discusses the critic that in general returns are not normally distributed. They propose to use the CVaR since it is a measurement that is reliable even in the absence of a normal distribution.

A paper published by Gass et al. (2011) evaluates risk for one wind site in the presence of wind speed uncertainty. Returns are defined as the internal rate of return computed from the annual free cash flows based on investment and operating expenses. Risk is defined as the CVaR at a confidence level of 0.9, 0.95 and 0.99 using a Weibull distribution. The analysis estimates long-term wind velocity for one potential wind site in Austria and finds that with a probability level of 0.95 the internal rate will not be lower than 7.6% and with a probability of 5% the internal rate will not be above 8.98%. The main contribution of this paper is the development of a statistical simulation method for wind energy production to better assess wind speed uncertainty. Although the scientist apply the CVaR for one wind site the approach does not focus on optimizing a portfolio of several wind sites.

Table 1 and 2 outline all publications including return measures, risk measurements and the information if wind or solar power has been added to a generation portfolio. The bold terms are the identified contributions to theory.

Authors	Application	Return measures	Risk	Wind	Solar
Return: **Levelized cost of energy**					
Awerbuch and Berger, 2003	**EU** Generation Portfolio	• Investment • Fuel • Variable and fix O&M *kWh per US cent*	Standard deviation	X	
Jansen et al., 2006	**Dutch** Generation Portfolio	• Investment • Fuel • Variable and fix O&M • **Environmental (CO_2)** *Euro per MWh*		X	**X**
Krey and Zweifel, 2006	**Swiss** & US Generation Portfolio	• Investment • Fuel • Variable and fix O&M • **Environmental (nuclear waste fee)** *Cost decrease (percentage)*		X US	X Swiss
Bhattacharya and Kojima, 2010	**Japanese** Generation Portfolio	• Investment • Fuel • Variable and fix O&M • Environmental (CO_2) *MWh per Dollar*		X	X
Delarue et al., 2011	**Belgian** Generation Portfolio	• Investment • Fuel • Variable and fix O&M • **Wind opportunity costs for capacity** *Euro per MWh*		X	
Return: **Net present value**					
Roques et al., 2006	UK Generation Portfolio	• Investment • Fuel • Variable and fix O&M • Environmental (CO_2, nuclear waste fee) *ENPV (pount m/GWe)*	Standard deviation	-	-
Return: **Energy output per installed capacity**					
Hansen 2005	**US** wind Generation Portfolio	• Annual wind energy generation *Capacity factor (output in kWh / installed capacity kW)*	Standard deviation	X	
Drake and Hubacek, 2007	**UK** wind Generation Portfolio	• Annual wind energy generation *Capacity factor (output in kWh / installed capacity kW)*		X	
Roques et al., 2010	**EU** wind Generation Portfolio	• Annual wind energy generation • **Wind energy generation during 10% of peak demand** *Capacity factor (output in kWh / installed capacity kW)*		X	
Rombauts et al., 2011	**Dutch** wind Generation Portfolio	• Annual wind energy generation • **Wind energy generation after transmission constraints** • *Capacity factor (output in kWh / installed capacity kW)*		X	

Table 1: Literature review: Mean-variance portfolio theory & energy sector

Authors	Application	Return measures	Risk	Wind	Solar
Return: **Internal rate of return**					
Borchert and Schemm, 2007	Dutch wind Generation Portfolio	• Investment • Variable and fix O&M *Percentage of invested capital (%)*	Conditional Value at Risk	X	
Gass et al., 2011	Austrian wind site	• Investment • Variable and fix O&M • *Percentage of invested capital (%)*		X	

Table 2: Literature review: Conditional value at risk & energy sector

The analysis of prior research allows to derive five research gaps within the renewable energy portfolio theory. First, very few approaches integrate wind as well as solar generation (table 2) and none of the discussed studies look at optimized shares between wind and solar. Second, although most of the publications assume a normal distribution of returns the discussion if there might be a misinterpretation of risk is neglected. Third, the application of portfolio theory based on a large Germany empirical dataset has never been focus of research. Fourth, the four research streams take only one perspective: either the technological to create ideal output portfolios or the political and investor perspective to create ideal cost efficient portfolios. The following section addresses how this dissertation closes the identified research gaps.

3.2. Closing the research gaps

3.2.1. The diversification effect

The literature review states that only three out of twelve publications integrate wind and solar generation in their portfolio approach. This is surprising since the characteristics of wind and solar generation seem to be diverse. Wind generates throughout a year in all hours of the day with the highest generation during winter month. On the contrary, solar generation takes place during day times especially in the summer months. Therefore, this paper argues that the cornerstone of portfolio theory - diversification - which is a concept of investing in different assets to minimize risk for a given return or to increase returns for a given level of risk can be used to optimize wind and solar portfolios. Risk is measured by the standard deviation and the covariance of two assets. Covariance $Cov(X,Y)$ outlines how two assets are correlated to each other and is calculated as the weighted sum of the multiplied deviations r_{xi}/r_{yi} of the expected asset returns $E(r_x)/E(r_y)$ weighted with the probability of occurrence p_i.

$$Cov(X,Y) = \sum_{i=1}^{n} \left[\left(r_{xi} - E(r_x)\right) \times \left(r_{yi} - E(r_y)\right) \right] \times p_i \tag{1}$$

The correlation coefficient between assets states the relationship and the degree they influence another. The diversification effect is measured by the correlation coefficient ρ.

$$\rho_{x,y} = \frac{Cov\ (r_x, r_y)}{\sigma_x \times \sigma_y}$$

(2)

The value ranges from -1 (returns move in the perfect opposite direction) to +1 (returns move perfectly in the same direction). In case there is no systematic relationship the quadratic relationship of the assets is not identified and therefore the coefficient is 0. The following figure outlines the relation between the returns of two assets.

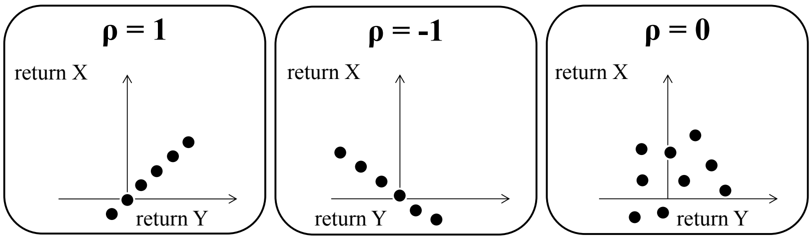

Figure 17: Correlation of positive, negative and non-related returns

The risk of a portfolio is lower than the sum of the weighted risk of the same assets. The portfolio risk strongly depends on the covariance of the assets, whereas the highest diversification effect is achieved by choosing for the same expected value assets that are perfectly negative related (Buchner, 1981). The expected value $E(r_p)$ of a portfolio is the sum of the weighted expected values of the different assets $E(r_i)$.

$$E(r_p) = \sum_{i=1}^{n} z_i \times E(r_i) \ whereas \sum_{i=1}^{n} z_i = 1 \ and \ z_i \geq 0, \forall\ i = 1, \dots, n$$

(3)

The variance of the portfolio ${\sigma_p}^2$ are the ${z_i}^2$ weighted variances ${\sigma_i}^2$ of each expected return and the weighted covariance $2z_iz_j$.

$$ {\sigma_p}^2 = \sum_{i=1}^{n} {z_i}^2 \times {\sigma_i}^2 + 2 \times \sum_{i=1}^{n-1} \sum_{j>i}^{n} z_i \times z_j \times Cov(i,j)$$

(4)

The diversification effect is able to reduce random risk. The combination of different assets results in a return variance room. The combination is efficient if there is no other combination at which either another combination represents a higher return for the same risk or the same return for a lower risk. All efficient combinations lie on the efficient frontier. In case a portfolio holds two different assets the portfolio risk can be expressed as:

$$\sigma_p{}^2 = z_i{}^2 \times \sigma_i{}^2 + z_j{}^2 \times \sigma_j{}^2 + 2 z_i z_j \rho_{i,j} (\sigma_i \times \sigma_j) \tag{5}$$

A lower correlation coefficient reduces portfolio risk. In case the coefficient is -1 the portfolio risk could be totally eliminated.

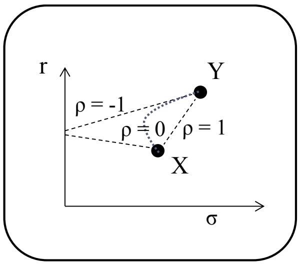

Figure 18: Portfolio returns (r) as function of portfolio risk (σ)

The ideal portfolio which lies on the efficient frontier is determined by individual human behaviour towards uncertainty (Simon, 1947). Even though all investors prefer higher returns over lower returns (Breuer et al., 1999), their investment decision is based on their risk behaviour. There are three categories of risk: risk averse, risk seeking and risk neutral behaviour (Copeland & Weston, 1988). Risk averse investors prefer assets that generate at any time a secured return over taking the risk of gambling and the chance of higher returns. Risk seeking investors are unconcerned with volatile returns since they value the opportunity to generate a return above expectation higher than the risk of ending up with a return below expectation. A neutral investor is indifferent between the two options.

The value of risk and return is thus weighted by the investor. The utility function outlines the compromise between risk and return. The function assigns to each expected value that is assumed to emerge at a probability p a profit whereas the bend of the curve depends on the investor preference. A concave utility function $U_{(r)}$ possesses risk aversion since a secured return is preferred over a unsecured return. Thus, an increasing return results in a decreasing final utility.

Each point between a straight line of two expected returns r_1 and r_2 is below the utility curve as illustrated in figure 19. The risk averse utility function $U_{(r)}$ for a share α within a portfolio of two assets can be describes as:

$$U_{(\propto r1+(1-\propto)r2)} \geq \alpha U_{(r1)} + (1-\propto)U_{(r2)} \tag{6}$$

A convex utility function $U_{(r)}$ characterizes a risk loving investor since unsecured returns are preferred over secured returns. An increasing return is associated with an increasing final utility. Graphically, drawing a line between two returns would result in data points that are all above the utility function. The formula for a risk seeking investor is thus:

$$U_{(\propto r1+(1-\propto)r2)} \leq \alpha U_{(r1)} + (1-\propto)U_{(r2)} \tag{7}$$

A linear utility function $U_{(r)}$ shows the behaviour of a risk neutral investor since there is no preference for one or the other option. An increasing return results in the equal final utility. The next graph shows a risk averse, a risk seeking and a risk neutral utility function.

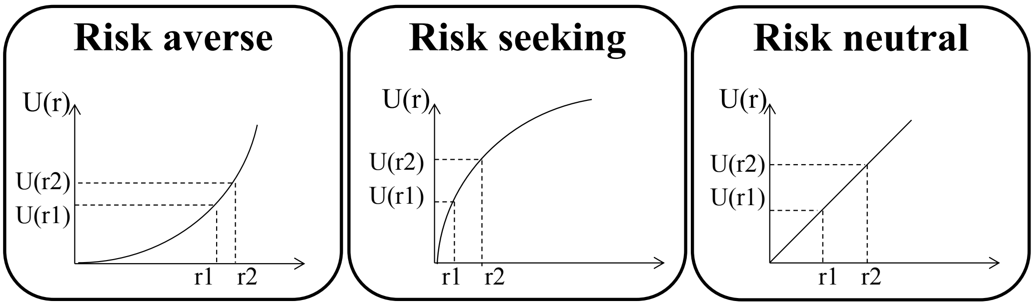

Figure 19: Utility functions of three different investors

In terms of entrepreneurial decision making a risk seeking or risk neutral behaviour is rare. Investors aim to maximize their assets while facing the lowest risk (Bernoulli, 1954) which means that the utility function outlines a rational decision making under uncertainty. Thus, most investors select assets that show the lowest risk for the same return (Neumann & Morgenstern, 1947) which is the key assumption for portfolio theory.

To sum up, this dissertation studies the diversification effect of wind and solar energy only which has not been evaluated in science, so far. Going in lie with other portfolio research in the energy sector, investors are supposed to act risk averse which indicates a rational decision making under uncertainty (Breuer et al., 1999).

3.2.2. Risk evaluation

As discussed in Chapter 3.1 to 3.4 three out of four research streams assume mean-variance portfolio theory originated by Markowitz (1952) but fell short on discussing if the empirical distribution approximates a normal distribution or if discrepancies result in a misinterpretation of risk. Their approaches assume that the equilibrium in which investors maximize an utility function depends solely on the frequency and variance of returns. The degree to which returns and risk vary is measured by the standard deviation of returns defined as the square root of its variance (Markowitz, 1952). This definition supposes that generated returns at capital markets are constant and therefore normally distributed. The characteristics of normally distributed returns is that in two out of three cases the return resides within the standard deviation of $\mu\ \pm 1\sigma$. In ninety-five out of one hundred times, the return is within two standard deviations $\mu\ \pm 2\sigma$ as outlined in figure 20 (Dubacher & Zimmermann, 1989). The usage of variance as a risk measurement is appropriated in case the underlining return distribution is normal and symmetric while upside and downside risk are disliked by investors (Estrada, 2007). Based on the assumption that investors associate risk with the probability of earnings less than the expected return it is more intuitive and economic reasonable to define risk as negative deviations only (Imboden, 1983).

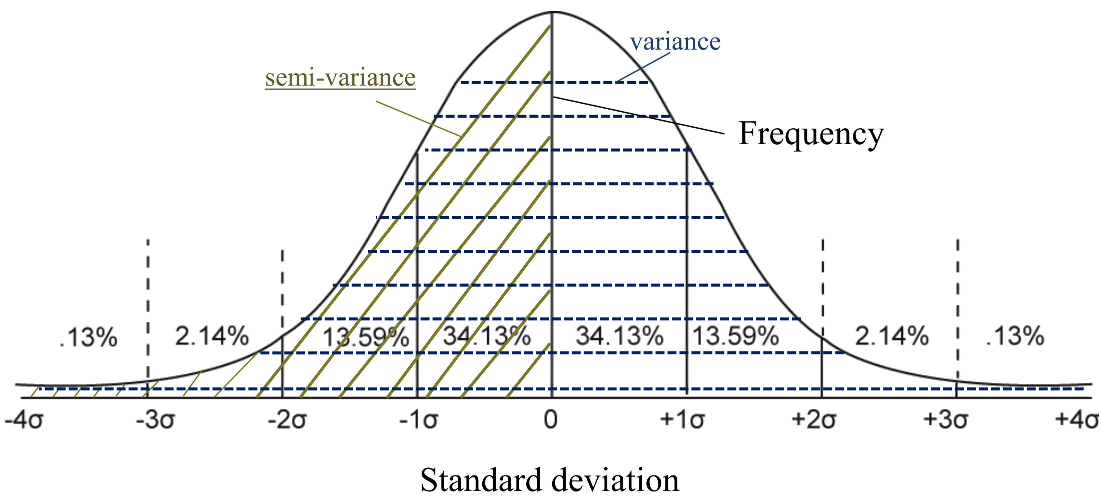

Figure 20: Risk measurements (variance and semi-variance)

Post-modern portfolio theory defines risk as the standard deviation of the semi-variance to capture downside risk only (Bawa, 1975). However, it has not been applied within the renewable energy portfolio theory research, so far. Semi-variance assumes that positive deviations are additional returns instead of a threat of losses (Wittmann, 1959) and generate useful findings in case the underlying return distribution is asymmetric (Fishburn, 1977).

Several studies find that even though the calculations are far more complex, the results show the same accuracy as returns being symmetrical distributed (Markowitz, 1992; Byrne & Lee, 2004; Grootveld & Hallerbach, 1999). Thus, this dissertation concludes that a semi-variance approach for wind and solar generation data is not superior to using a mean-variance approach. Considering the variance as a risk measurement is of course a simplification but valid if there are reasons for normally distributed returns, a quadratic utility function or an irrelevance of higher moments for an investor's decision (Rubinstein, 1973). In case none of these apply, early research in the finance sector developed conditions that would lead to mean-variance theory being ideal (Elton & Gruber, 1997) either by making adjustments to the investor utility function (Tobin, 1958) or on alternative portfolio theory approaches including higher moments (Kraus & Litzenberger, 1976). Under the assumption that higher moments of the return distribution are relevant for investor's decision making (Samuelson, 1970; Kraus & Litzenberger, 1976; Prakash & Bear, 1986) the aim of such approaches is to describe the return distribution in a more accurate way (Fama, 1965). Most distributions vary from the normal distribution in two ways. First, they are asymmetrically distributed (Graz et al., 2012) and second, their probability at the ends and in the middle is higher.

The asymmetry of a probability distributions depends on the balance of extreme values and can be measured as the skewness. The skewness is the third moment of a distribution and zero for a standard distribution. A negative skew indicates a left skewed probability distribution in that the negative values dominate resulting in an underestimation of risk (Canela & Collazo, 2007). In case positive skew exists, the distribution is right skewed and the assumption of a standard deviation leads to an overestimation of risk. Investors prefer positive skewness of a distribution (Lai, 1991; Chunhachinda et al., 1997) which is consistent with decreasing the probability of large negative returns (Arditti, 1967). Therefore absolute risk aversion is decreased. In presence of high positive skewness investors are even willing to accept negative expected returns (Campbell & Siddique, 1999/2000). Research about skewness has been widely performed for stock market returns (Kim & White, 2004; Canela & Collazo, 2007) but has not been used for wind and solar generation data although it might yield valuable insights about historical distribution characteristics.

The fourth moment, kurtosis, gives an indication for the probability at the ends and in the middle of a distribution (Ruppert, 1987). It is a measurement that describes the existence of extremes no matter if balanced or not and measures fat tail characteristics. The kurtosis of a standard distribution is zero and defined as the excess kurtosis. In case excess kurtosis is above zero, the distribution has fatter tails and a more acute peak which implies undesirable tail risk. Risk is represented by extreme values since the probability mass in the ends is bigger compared to a normal distribution (Balanda & MacGillivray, 1988; DeCarlo, 1997). Thus, the standard deviation underestimates the likelihood of extreme events. A negative excess kurtosis overvalues extreme events and indicates a lower, wider peak around the mean as well as thinner tails.

Some researcher argue that since kurtosis cannot be behaviourally justified it should be ignored (Kraus & Litzenberger, 1976; Prakash & Bear, 1986) although it might give at least a good indication for risk over- or underevaluation.

As prior research, this dissertation assumes that returns are normally distributed based on the argument that a distribution with an increasing number of variables approaches always a normal distribution (Hackl & Katzenbeisser, 1994). Since it has been found that skewness and excess kurtosis are measurements that give an indication of how distributions differ from a normal distribution, this research project adds to the statistical discussion and measures skewness and excess kurtosis for all wind and solar distributions. Both measurements enable a more in depth discussion about the potential of misinterpreting risk when using mean-variance portfolio theory. Figure 21 outlines the four moments and the risk misinterpretation in case skewness and excess kurtosis differ from zero.

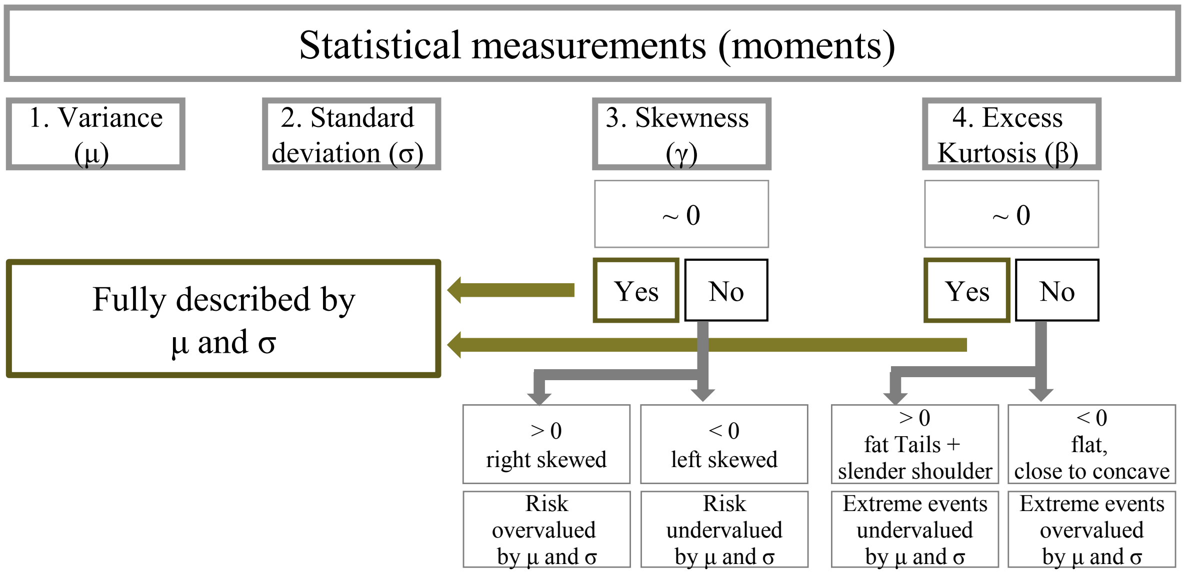

Figure 21: Statistical measurements (moments)

In addition to the method of capturing risk by higher moments, researchers propose probability risk measurements to optimize portfolios, e.g. the Value at Risk (VaR) which is a measure that refers to the expected gain-confidence limit criterion (Baumol, 1963). It measures market risk and is based on a quantile of a distribution (Jorion, 2001). A confidential level 1-α defines how often the command variable is below or above the VaR. The lower the risk seeking the higher the confidence level. The measurement examines one specific point of the negative deviation and defines the maximal loss of the worst scenario within a holding period and a confidence level of 1-α at a defined probability α. However, the VaR does not represent the risk that can be associated with the extreme values that exceed the confidence level. In case the ends are not normally distributed this measurement does not capture the risk in an adequate way. Stress tests and sensitivity analysis are methods to better understand the impact of the risk caused by fat tails below 1-α. Value at Risk estimates are difficult to predict since the data might be either time depending, asymmetric, skew or fat tailed (Mandelbrot, 1963). In addition to this, scientists find that the confidential level must be chosen carefully since if it is too small the VaR may not exist (Alexander & Baptista, 2002). VaR has not been discussed for wind and solar generation distributions. Although 1,550 articles are identified when searching the science direct database in late 2012, only five articles combine the energy sector and the VaR. Two publications discuss electricity spot prices, the third publication discusses oil prices and the fourth gas prices (Chan & Gray, 2006; Yau et. al, 2011; Marimoutou et al., 2009; Thaler et al., 2005). The fifth study uses the VaR to determine biofuel investments (Chang et al., 2011). This dissertation assumes that based on the limitations of the VaR other probability measurements are likely to be better measurements to capture risk that might be comprised in wind and solar distribution tails.

The Conditional Value at Risk (CVaR) is the expected loss in case the value at risk is exceeded (Krokhmal et al., 2001) and considers fat tails in the underlining assumption. The advantage over the Value at Risk is that the Conditional Value at Risk is a reliable risk measurement even if the distribution differs from a normal distribution. The measurement is asymmetric, defined as the weighted average of VaR (Rockafellar & Uryasev, 2000) and represents with the probability α the expected value of losses that are bigger than the value at risk. Experiments show that the minimization of CVaR leads to almost ideal VaR results for low skewed distributions. In case the return-loss distribution is normal the two measurements are equal (Rockafellar & Uryasev, 2000). Since this is likely not to be the case, the optimization of these two risk measures results in different portfolios since the CVaR controls losses exceeding the VaR (Gaivoronski & Pflug, 2000). The CVaR has one advantage over the VaR. It is the only coherent measure that satisfies the four properties monotonicity, sub-additivity, homogeneity and translation invariance (Artzner et al., 1999).

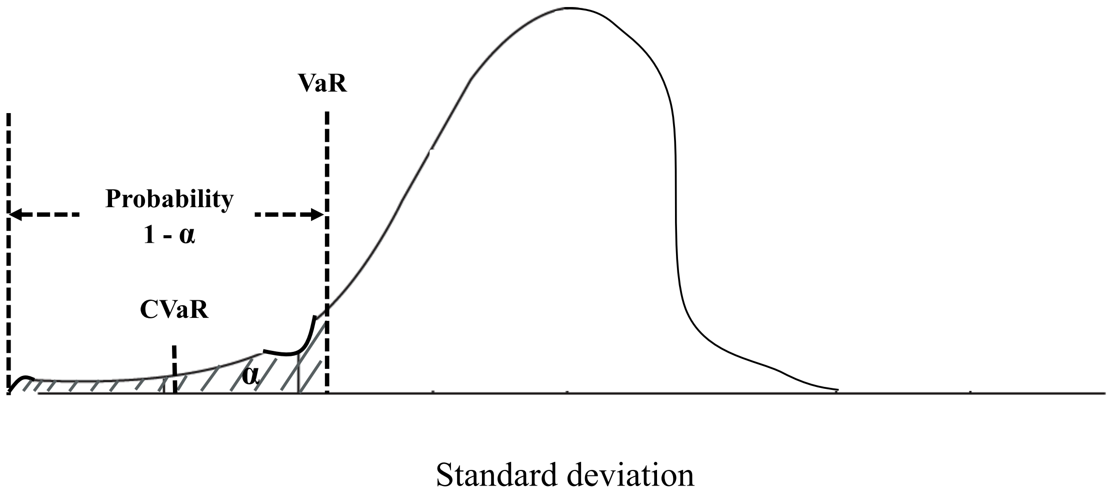

Figure 22: Probability measurements (VaR and CVaR)

The investigation of 850 articles related to portfolio theory, CVaR and renewable energy on the science direct database identifies one new publication in this field. This research paper applies the CVaR to determine optimal day-ahead bids for wind power producers to optimize profit (Botterud, 2012). The result indicates that the publication by Borchert and Schemm (2007) seems to be the only study using the Conditional Value at Risk to determine optimized wind portfolios.

Although this dissertation believes that the CVaR is a good probability risk measurement to extend the findings generated by using mean-variance portfolio theory it is far beyond this dissertation. The next table gives an overview of the discussed risk measurements and their relevance for this study.

	Mean-Variance Portfolio Theory	**Semi-Variance Portfolio Theory**	**Value at Risk**	**Conditional Value at Risk**
Risk capturing	Downside & upside risk	Downside risk	Downside risk	Downside risk
Risk measurements	Standard deviation	Standard deviation	Value at Risk at 1-α level	Conditional Value at Risk at 1-α
Coherent	no	no	no	yes
Relevant to risk measurement	yes	no	no	yes
In scope of this dissertation	**yes**	no	no	no

Table 3: Overview risk measurements

3.2.3. Integrating three perspectives

The framework developed in Chapter 2 suggests to integrate all three perspective (political, technological, investor) to address the topic that governments often tend to take a short-term perspective. Thereby, the value of generation technologies is derived solely from energy generation costs neglecting potential costs concerning system security in the long-term. Such costs are defined as balancing and capacity costs and are very likely to increase their impact on total system costs with an increasing share of wind and solar power in an energy system. Given that policy makers define progressive renewable energy goals, it is surprising that we know so little about long-term cost efficient portfolios. Nor can we say how the share between wind and solar impacts the technological as well as political and investor perspective in the long-term. Conclusively, this dissertation adds balancing and capacity costs to the levelized cost of energy method to optimize wind and solar portfolios from a technological, political and investor perspective.

3.3. Overall strategy and approach

To sum up Chapter 3, this dissertation adds to theory in four ways. First, by combining the assets wind and solar power, this thesis responds to the call of examining the correlation and thus the diversification effect between wind and solar generation (Drake & Hubacek, 2007). Second, it is accepted that mean-variance portfolio theory has been a commonly used approach to identify ideal portfolios in the energy generation sector. This dissertation argues in line with other scientists that an increasing number of variables approaches always a normal distribution (Hackl & Katzenbeisser, 1994). In addition to this, the knowledge about wind and solar distributions is broadened by examining the skewness and excess kurtosis for a large wind and solar dataset (Hansen, 2005). This might generate details about the potential of risk misinterpretation using the underlying assumption of a normal distribution. Third, it is the first study that applies portfolio theory to a large German wind and solar generation and forecast data set (total of 105,120 data points). Fourth, it adds to the commonly used levelized cost of energy method (political and investor perspective) that focuses either on costs (first, second, third research stream) or on energy outcome per installed capacity (fourth research stream) by integrating balancing and capacity costs (technological perspective). This dissertation is an innovative, exploratory contribution to currently discussed energy policy topics. Thus, the definition of different risk measures should be seen as a first step in wind and solar portfolio theory research.

4 German Case Study

The overall chapter is structured into three parts. First, the predictability, volatility, contribution to peak demand and the generation output expressed as capacity factor for German wind and solar generation datasets are examined for the years 2010 to 2012. The characteristics of the distributions of the four elements is visually and statistically tested. It is discussed to which degree the distributions follow a normal distribution. In the second part, the theoretical framework is used to develop efficient wind and solar portfolios that maximize predictability, minimize volatility, maximize contribution to peak demand and minimize total system costs. The reliability of the results is addressed by performing a sensitivity analysis before conclusions are drawn.

Figure 23: Overview German Case Study

4.1. Empirical analysis

4.1.1. Sample

Wind and solar generation in Germany is financially supported by the society paying the renewable energy allocation fee. Therefore, publishing of generation and forecast data is required. The empirical data of 12-hour day ahead forecast and generation in the time period from January 2010 to December 2012 is drawn from five different sources: the eex transparency platform and four databases of the German grid operators that are responsible for daily publishing (amprion, TransnetBW, Tennet TSO, 50Hertz Transmission). The sample is obtained by merging the fifteen minute data from the grid operators from January 2010 to June 2010 and the eex transparency platform data from July 2010 to December 2012. It should be noted that it is likely that the solar data in the timeframe January 2010 to June 2010 has been only partially published since central publication by law started to be required in June 2010. Based on the approach used by Holttinen (2005), this dissertation converts the fifteen minute time series into an hourly sample resulting in subsequent 26,280 data points for wind forecast, solar forecast, wind generation and solar generation data. Equal to other studies, it is argued that by evaluating historical data inferences can be made about recurring event-types although there is a small likeliness that actual events reappear (Ibbotson Associates, 1998). Therefore, the thesis states that even though the duplication of such events will not happen, historical variability is widely considered to be a good indicator for future volatility (Awerbuch & Berger, 2003). The decision if a portfolio is ideal or not is based on the optimal trade-off between the mean and the variance determining the portfolio return in the future period (Markowitz, 1952). The time period for which data is collected impacts the expected single-period returns of the analysis. Little research has been conducted on the appropriate length of a single-period solution (Elton & Gruber, 1997) although this is crucial to determine optimal portfolios. This dissertation performs a single period analysis based on a timeframe of three-years since the complexity of non-linear models rebuilding wind and solar generation patterns go far beyond this approach and should be matter to further research[2]. The determination of optimized portfolios is based on the assumption of a risk averse investor. Thus, optimized portfolios are assumed to be the portfolios which illustrate the lowest risk. This thesis includes night and day forecast and generation data. This method is commonly used for wind portfolio theory research. Since no solar portfolio theory research has been performed so far, this dissertation applies the method used for wind to solar energy. One may argue there are differences in the solar generation pattern between night and day. This would require to examine ideal night and ideal day portfolios or exclude night hours. Others may argue that first, the definition of hours which should be excluded is unclear; second, the comparison between 8760 data points for wind per year and only about half the data points for solar is a comparison of apples and pears; and third, although there might be different theoretically ideal day and night portfolios the energy system can drive towards one portfolio, only. Although this paper is aware that the pursued method is just one way to calculate ideal portfolios, other approaches should be matter to further research.

[2] Critics argue that the assumption that one period models of future events replicate the past is not always true. Multi-period approaches aim to overcome this problem by using a sequence of single period problems (Steinbach, 1999). Also, non-linear approaches such as Monte Carlo simulations are used to model reality to calculate the likelihood of future risk and return (Binder, 1979).

4.1.2. Measures

The dissertation derives from the theoretical framework four measures, namely predictability error [1], volatility [2], contribution to peak demand [3] and levelized cost of energy [4]. The first three measures are used to find ideal technological portfolios, the fourth measure is utilized to calculate optimal total cost portfolios.

The first measure is defined as the predictability error [1] of wind and solar generation between 2010 to 2012. Hourly predictability is a crucial factor for short-term balancing risk (Delarue et al., 2011). A high predictability indicates low balancing costs. The predictability error is computed as the absolute error PE_t between the forecasted values $x_{1,t}$ and actual generation values $x_{2,t}$:

$$\Delta PE_t = (x_{2,t} - x_{1,t}) \tag{8}$$

Wind and solar power is underpredicted in case the actual value is higher than the forecasted value. Vice versa, if the actual generation is higher than the forecast, the power generation is overpredicted. Both situations are assumed to be suboptimal for the system since they relate to balancing needs to maintain system security. The predictability error PE_t is defined as percentage of installed capacity I_c in the specific year:

$$PE_t = \frac{\Delta PE_t}{I_c} \tag{9}$$

After calculating the predictability error data set PE_t for each technology, the variance room is created by calculating for each combination of wind and solar the average output and the standard deviation (formula 5). The average output is the predictability error, the standard deviation of the predictability error defines the risk.

The second element volatility [2] is investigated for the hour to hour volatility. It is of interest for system security in terms of mid-term balancing (Gross et al., 2006). The lower the volatility either in a positive or in a negative way the lower the need for balancing (Katzenstein & Apt, 2012). Volatility depends on geographical conditions and ranges between an annual minimum and maximum value. The dataset is calculated by expressing delta volatility Δv_t as the power difference between the generation in P_t and the power generation in the previous hour P_{t-1} (Holttinen, 2005):

$$\Delta v_t = P_t - P_{t-1} \tag{10}$$

Volatility V_t is expressed as the volatility delta defined as percentage of installed capacity I_c in the specific year:

$$V_t = \frac{\Delta\, v_t}{I_c} \tag{11}$$

The variance room for volatility is developed by calculating the average output and the standard deviation (formula 5) for each combination of wind and solar. The output represents the volatility, the standard deviation defines the risk.

The contribution to peak demand [3] is the third measure and relevant for the energy system since it determines the required capacity to ensure system security. A high contribution to peak demand results in low additional capacity needs. Peak demand is defined as the 10% of highest demand throughout one year (Roques et al., 2010) which limits the examination to the highest 876 hours. In the first step, the 876 hours of the highest peak demand for each year are extracted. Then, the percentage of each, wind and solar contribution in these peak hours is calculated.

The contribution C_t is computed as the power generation P_t as percentage of total demand D_t.

$$C_t = \frac{P_t}{D_t} \tag{12}$$

The variance room for the contribution to peak demand is developed by calculating the average output and the standard deviation of all wind and solar portfolio combinations. The output is the contribution to peak demand, risk is defined as standard deviation.

Differing from the technological optimized portfolios, the fourth portfolio focuses on a financial measurement: the levelized cost of energy [4]. The levelized cost of energy (LCOE) approach expresses average generation costs of a technology over its lifetime. Costs and expected electricity generation is discounted, potential realized prices within a market are ignored. The levelized cost of energy approach has been widely used to compare generation technologies (WEO, 2000) and appears to be a valid measure to determine costs in the long-term.

First, the annuity AN of the initial debt D and the interest rate i over the financing time N is calculated as:

$$AN = D \times \frac{i \times (1+i)^N}{(1+i)^N - 1}$$

(13)

Then, the residual annual debt RD_n is calculated as follows:

$$RD_n = RD_{n-1} - (AN - (RD_{n-1} \times i\,))$$

(14)

After adding the operation O_n, balancing B_n and capacity C_n expenses for each year, the total life cycle costs are calculated as the sum of the expenses cash flows discounted with the discount rate d:

$$TDLCC = \sum_{0}^{N} \frac{AN + O_n + B_n + C_n}{(1+d)^n}$$

(15)

In the next step, the energy yield is calculated by multiplying the capacity factor CF of the generation plant with its system size SS. The average annual capacity factor CF is expressed as power P as a percentage of total installed capacity I:

$$CF = \frac{P}{I}$$

(16)

A degradation factor df is integrated to include efficiency losses. The energy output is then discounted to the initial year as follows:

$$TDEY = \sum_{0}^{N} \frac{(CF \times SS) \times (1 - df)^{n-1}}{(1+d)^n}$$

(17)

The levelized cost of energy (LCOE) is then calculated as:

$$LCOE = \frac{TDLCC}{TDEY}$$

(18)

Since the levelized cost of energy is assumed to be equal in each hour of the year, the wind and solar generation distribution is equal to the levelized cost of energy distribution. Therefore, the wind and solar generation distributions are examined by calculating for each hour t the power P_t as a percentage of total installed capacity I_c in the specific year:

$$CF_t = \frac{P_t}{I_c} \tag{19}$$

After calculating the capacity factor data set CF_t for each technology, the variance room is created by multiplying the capacity factor data with the inverse levelized cost of energy data. Then, for each combination of different wind and solar portfolios, the return and the standard deviation (formula 5) is computed. Return is defined as the generated kilowatt-hours per Euro, the standard deviation is defined as risk.

All four measurements are plotted in a histogram. In addition to this, the third moment, skewness S is defined as:

$$S = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^3}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2\right)^{\frac{3}{2}}} \tag{20}$$

When $\bar{x}$ is the sample mean for a sample of n values. As discussed before, the skewness of a normal distribution is zero. Higher values indicate a risk overevaluation since there is more probability mass in the downside risk. On the contrary, lower values underevaluate risk due to a higher probability mass in the upside risk.

In the next step, the kurtosis K is computed for a sample n for all four data series as:

$$K = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^4}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2\right)^2} \tag{21}$$

The kurtosis of a normal distribution is three. Excess kurtosis which is zero for a normal distribution is defined by subtracting three from formula (15). In this paper, excess kurtosis EK is used to compare the dataset to the normal distribution:

$$EK = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^4}{(\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2)^2} - 3 \tag{22}$$

Values above zero indicate that extreme events are underestimated and vice versa, values below zero overestimate extreme values in the tails. However, excess kurtosis does not give an indication if extreme values are a downside risk, a upside risk or even level out.

After calculating skewness S and excess kurtosis EK, this publication performs the Jarque Bera normality test which tests whether a dataset is normally distributed. The statistic is based on skewness S and kurtosis K and is a two-sided goodness-of-fit test (Jarque & Bera, 1987). The test follows a chi-squared distribution with two degrees of freedom under the null hypothesis of a normal distribution. In case the statistic is below 5.99 the null hypothesis of normality can be supported at a 5% significance level. The statistical measure is computed as:

$$JB = \frac{n}{6}\left(S^2 + \frac{1}{4}(K-3)^2\right) \tag{23}$$

where n is the number of observations.

The next four sections are organized as follows: the four statistical measurements are evaluated. It is determined if skewness indicates a risk misinterpretation and if excess kurtosis is evidence for under- or overestimating extremes in the tails. Afterwards, the historical distributions are plotted. This analysis uses raw data instead of log returns although the awareness exists that log returns might fit a normal distribution better (Aitchison & Brown, 1957). However, the selected proceeding simplifies to interpret the results. QQ-plots for each dataset are attached in appendix (C). Lastly, results are compared to prior publications before the findings of each sections are summarized.

4.1.3. German dataset of technological measures

4.1.3.1. Wind and solar predictability error data 2010 to 2012

The predictability error from hour to hour is of interest for system security in terms of short-term balancing. The wind absolute predictability error for 1-day ahead forecasts ranges between ±10% as illustrated in figure 24. Nevertheless, there are six times of high wind forecast errors. Under the visual examination these errors seem to occur randomly within the examined timeframe.

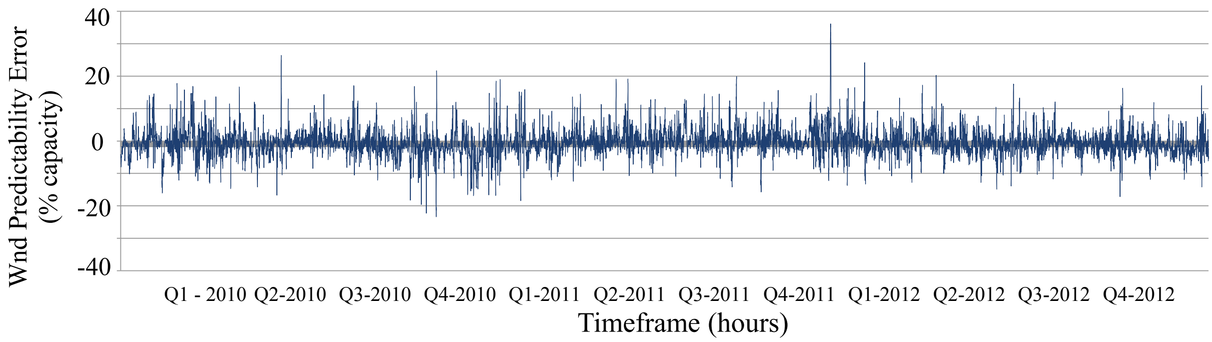

Figure 24: German wind hourly predictability error 2010 to 2012

The solar errors in figure 25 in the timeframe January to May 2010 differ compared to forecast errors between June 2010 to December 2012. They vary more often within a corridor of ± 10%. Extreme values higher than 20% are by far less than for wind power (excluding the data series at the beginning of 2010). As already observed for wind energy, extreme errors seem to occur from time to time randomly throughout a year.

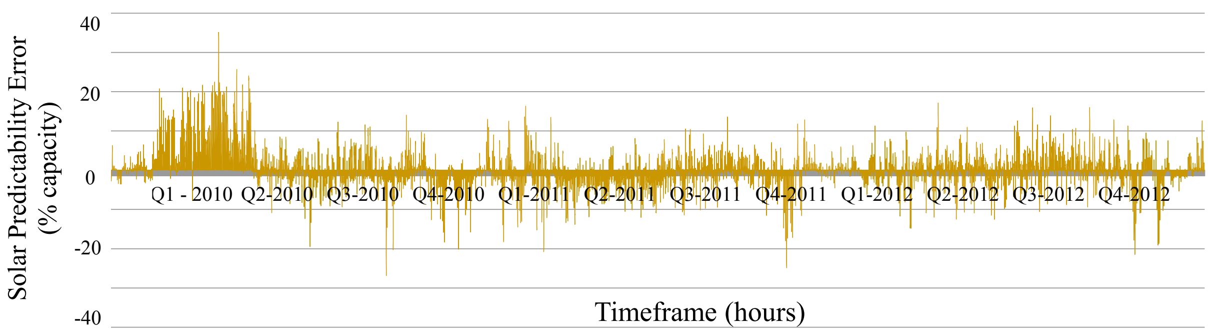

Figure 25: German solar hourly predictability error 2010 to 2012

The duration curves of predictability errors show that there are extreme positive errors. Generation is highly undervalued for both technologies. The extreme positive wind predictability errors are as high as 35% in 2011 but decrease in 2012 to the 2010 level of 25%. The maximum of negative wind error is reduced during 2010 to 2012 from -23% to -15%. The positive solar predictability error is 35% in 2010 and is diminished in 2011 and 2012 to 16%. The negative value is minimized from 2010 to 2012 from -27% to -21%. The analysis shows that all three-years excluding the beginning of 2010 indicate equal characteristics.

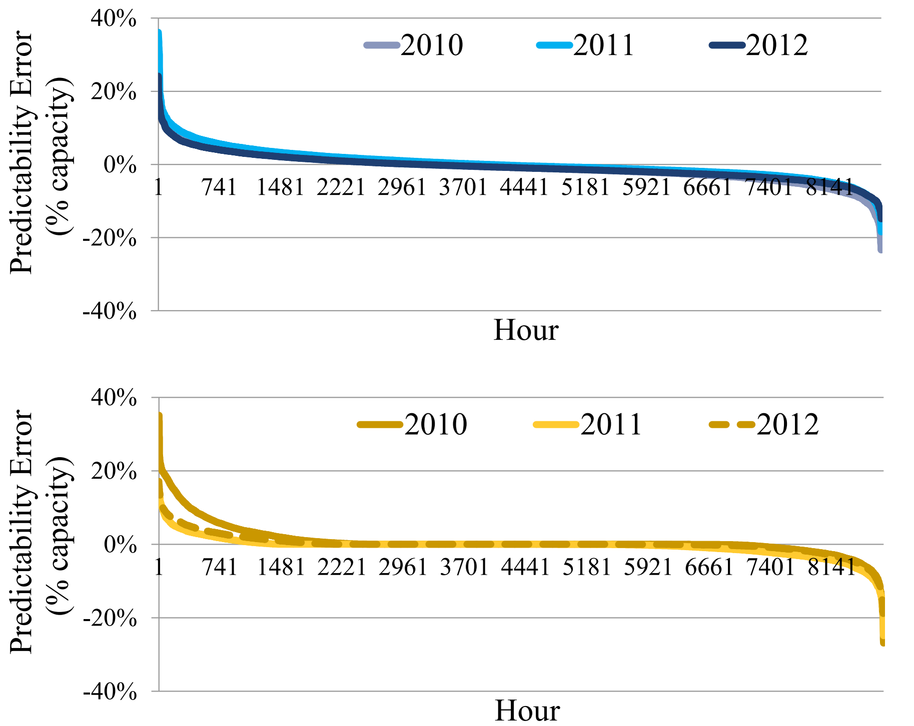

Figure 26: Duration curve - German wind & solar hourly predictability error

The mean of predictability errors can either be negative or positive. Both situations are assumed to be equally suboptimal and therefore result in the same degree of balancing costs for the energy system. The wind dataset of 2010 to 2012 (26,280 data points) indicates a mean of $-4.4*10^{-3}$ and a standard deviation of 0.041. The mean of solar data in this timeframe is $8.3*10^{-4}$ with a standard deviation of 0.0011. Based on the assumption of risk averse investors preferring minimal risk over maximal return the first hypotheses is formulated:

H1: The optimal predictability error portfolio holds based on a lower solar standard deviation a higher share of solar compared to wind energy

The wind skewness of 2010 to 2012 is 0.7012. In the same timeframe, solar skewness is recorded to be 1.1603. Hence, risk is overestimated in both cases under the assumption that downside risk is worse than upside risk. Downside and upside risk of the predictability error data set are both disliked by investors. Thus, skewness might lead to a risk misinterpretation.

The excess kurtosis of wind for 2010 to 2012 data is 5.36, the solar excess kurtosis is recorded to be almost three times higher with a value of 12.95. Therefore, wind and solar distributions for all years are found to be leptokurtic, thereby undervaluing extreme events in the tails compared to a normal distribution.

To collect details about the 5% most extreme positive and negative values enhances the understanding of extreme events. Thus, the highest and the lowest 1,314 values are summed up and divided by the total number of data points (2,328). It is found that for wind as well as for solar predictability errors a probability mass in the upside risk exists (0.00079 and 0.01151). This said, more positive extremes are recorded. Figure 27 shows the positive and the negative deviations of the most extreme ±5%.

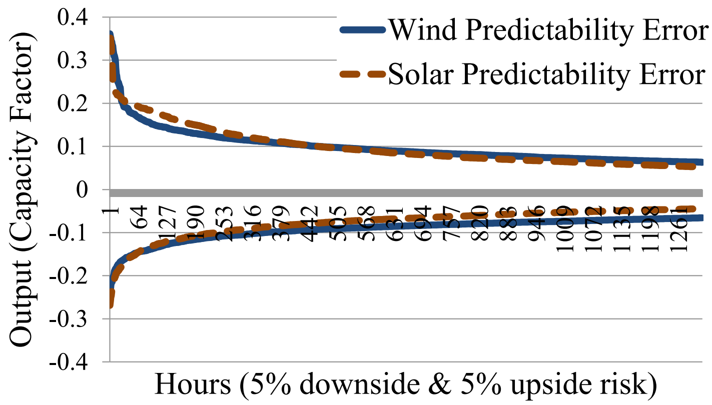

Figure 27: Tail analysis: predictability error ±5% of extreme values

In the last step, the Jarque Bera test for the row data series of wind and solar reject normality for all years (appendix (A)). Findings by Florita et al., (2012) for 30,000 wind locations in the United States propose the assumption of a hyberbolic predictability distribution. Solar error predictability distribution research is very limited and does not propose a specific distribution. The dissertation plots the probability distributions for wind and solar in figure 28 a), b).

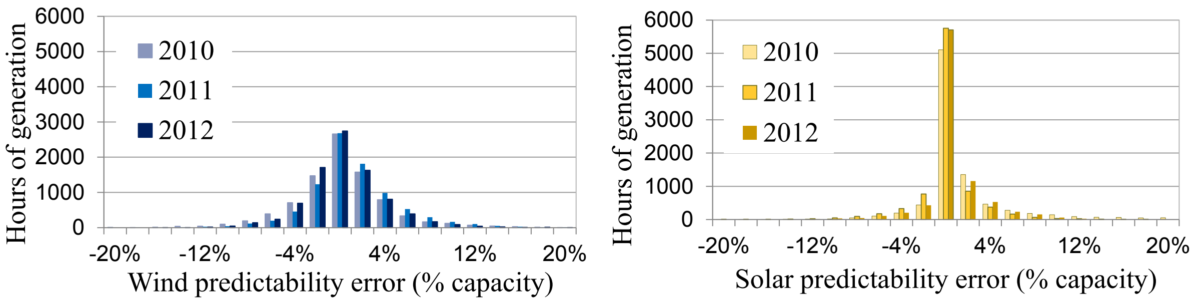

Figure 28a), b): Wind and solar predictability error distribution 2010 to 2012

Summarized, there are three findings. First, the predictability error of wind ranges between ± 10%, solar ranges between ± 20%. Second, the lower standard deviation of solar is very likely to lead to a higher solar share in the optimized predictability error portfolio. Third, extreme values in the tails are small. In this dissertation, the discussed distributions are used to identify theoretical optimal portfolios that minimize predictability errors and minimize risk defined as the variability of predictability errors. Despite the awareness that the data does not totally fit a normal distribution mean-variance portfolio is used for portfolio development.

4.1.3.2. Wind and solar volatility data 2010 to 2012

The hourly volatility is of interest for system security in terms of mid-term balancing. Figure 29 illustrates the difference from one to the next consecutive hour. Wind volatility ranges from 10% to -10% as percentage of installed capacity.

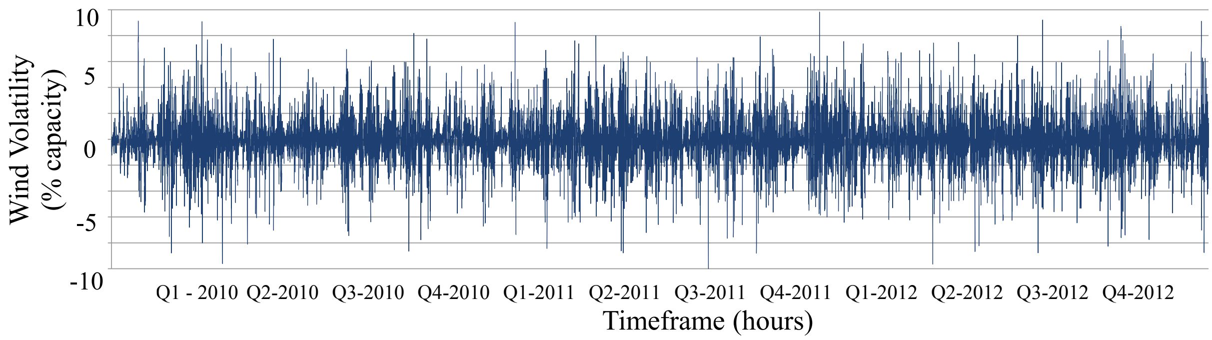

Figure 29: German wind hourly volatility 2010 to 2012

The volatility of solar in figure 30 is not as consistent as wind energy volatility. As expected, the visual observation indicates that the highest volatility is in summer times (15%), the lowest in winter times (5% to 10%).

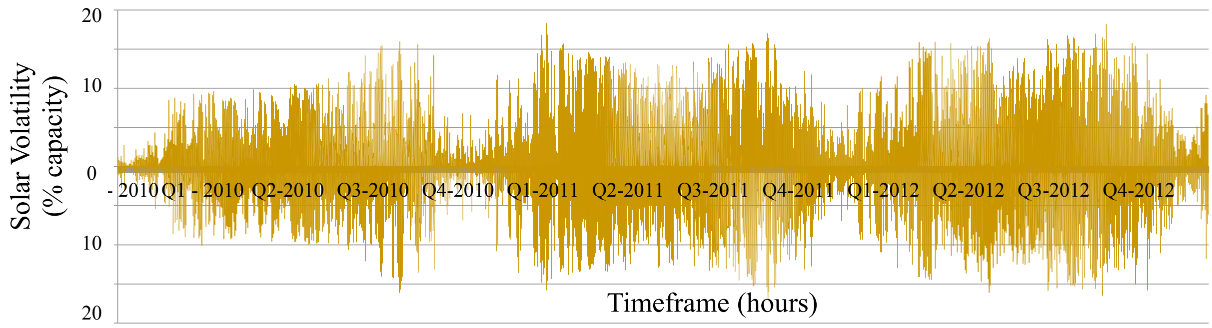

Figure 30: German solar hourly volatility 2010 to 2012

The duration curves (figure 31) of wind and solar from 2010 to 2012 outline that wind volatility in the three-years have equal characteristics. No wind volatility is recorded for 3,453 hours in 2010, 3,075 hours in 2011 and 2,868 hours in 2012. The 2010 solar duration curve differs from the 2011 and 2012 curves. The times of zero solar volatility is identified to be higher than for wind with 4,673 in 2010, 4,288 in 2011 and 4,225 hours in 2012. The analysis shows that although solar energy generates in 50% less hours than wind, the volatility is only 25% lower.

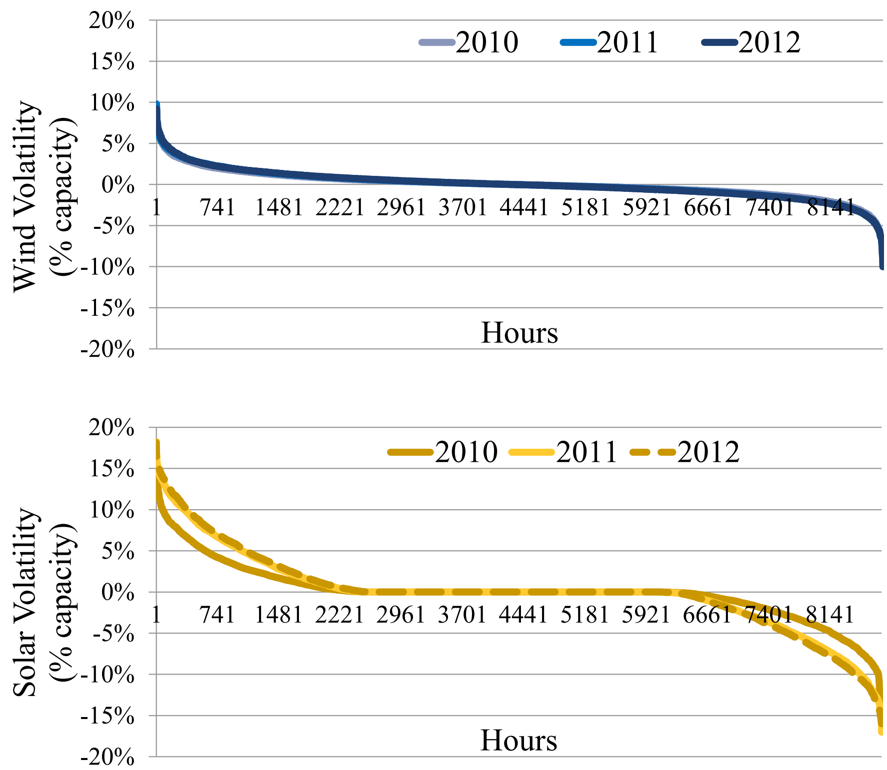

Figure 31: Duration curve - German wind and solar hourly volatility

The mean of wind volatility (2010 to 2012) is with $1.9*10^{-5}$ twice as high as the mean of solar volatility of $1.0*10^{-5}$. As displayed for the first measure, both variations (negative and positive) are disliked since it is assumed that they result in the same level of mid-term balancing costs. A lower wind standard deviation (0.017) compared to solar standard deviation (0.043) is the foundation for the second hypothesis:

H2: The optimal volatility portfolio holds based on a lower wind standard deviation a higher share of wind compared to solar energy

Wind and solar skewness for 2010 to 2012 are 0.0651 and 0.1668. As discussed before, neither downside nor upside risk is preferred. The values are likely to lead to a misinterpretation of risk.

Excess kurtosis for wind is 3.01 and therefore, higher than excess kurtosis for solar (2.31). The distributions are found to be leptokurtic, thereby undervaluing extreme events when assuming a normal distribution in all years for both technologies. The 5% fat tail analysis that outlines the averaged sum of the 1,314 highest and lowest values shows that wind balances out with a value close to zero ($6.5*10^{-5}$) compared to the mean of $1.9*10^{-5}$ (absolute deviation of $4.6*10^{-5}$). The solar analysis indicates a value of $3.44*10^{-3}$ compared to the mean of $1.0*10^{-6}$ (absolute deviation of $2.44*10^{-3}$). Figure 32 shows the variation in the hours of the highest and lowest 5%.

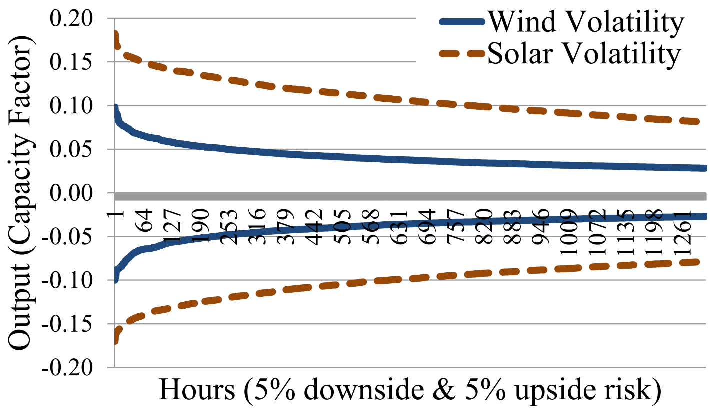

Figure 32: Tail analysis: volatility ±5% extreme values

Prior research on wind kurtosis is limited but findings that have been generated in the United States for solar kurtosis go in line with this study (Hodge et al., 2011). Models that capture wind and solar distributions are proposed in science. Goic et al., (2010), for instance, examine wind volatility distributions on an annual basis and analyze aspects of Markov chain Monte Carlo simulation to model wind volatility distributions. However, they find that these approaches are not adequate to model stochastic dependencies between wind power time series. They propose a second-order Markov chain Monte Carlo simulation which allows to model synthetic time series of aggregated wind power that closely fits original data. Although publications of annual solar distributions are still scare in science, Hodge et al., (2011) report that solar volatility distributions are significantly non-normal over timescales from 1 minute to 1 hour. They propose an hyberbolic distribution to capture high leptokurtosis. The Jarque Bera test supports these findings and indicates that neither wind nor the solar volatility distributions fit a normal distribution (appendix (A)).

The probability distributions (figure 33a), b)) display that for wind and solar, the probability in the middle is higher in comparison to a normal distribution. Similar findings are identified for wind volatility by Holttinen (2005), Roques et al., (2010) and Goic et al., (2010) who observe distributions of other European countries.

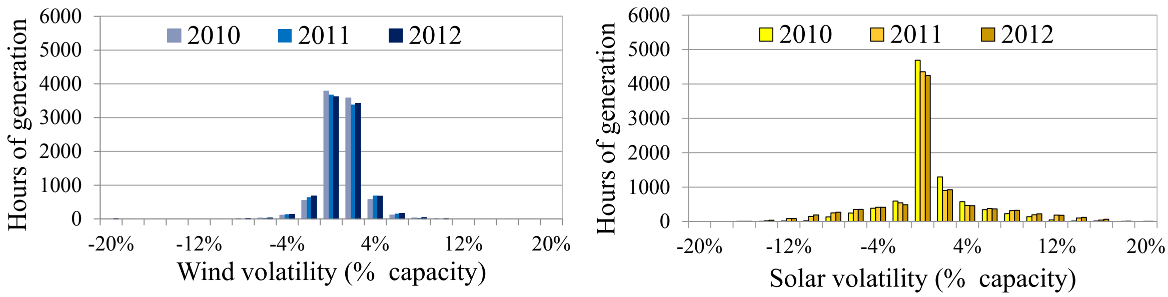

Figure 33a), b): Wind and solar volatility distribution 2010 to 2012

Three outcomes of the volatility evaluation are recorded. First, the volatility of wind is fairly stable and ranges between ± 10%. On the contrary, solar volatility differs based on the season of the year. Second, the low wind standard deviation is likely to overbalance wind in the volatility portfolio. Third, risk comprised in the tails for wind and solar is small. The dissertation assumes the distributions outlined in figure 33a) and b) to be normal and identifies optimal minimized volatility portfolios minimizing the variability of volatility.

4.1.3.3. Wind and solar contribution to peak demand data 2010 to 2012

The contribution to peak demand is relevant for system security related to capacity. The 876 hours of peak demand are identified to occur most often between the end of October and the mid of March. Although they occur in different times during 2010, 2011 and 2012 the analysis shows that wind contributes on a constant bases for about 5% to 10% to peak demand. The highest contribution in December and January ranges from 30% to 35%. In 2011, wind generation contributes most often to peak demand. Figure 34 outlines the 8,760 hours of a year and the contribution of wind to the highest 10% hours of peak demand. Therefore, each data point is an hour of peak demand. The x-axes shows in which hour of the year peak demand occurs within the system. The level of wind contribution is plotted on the y-axes.

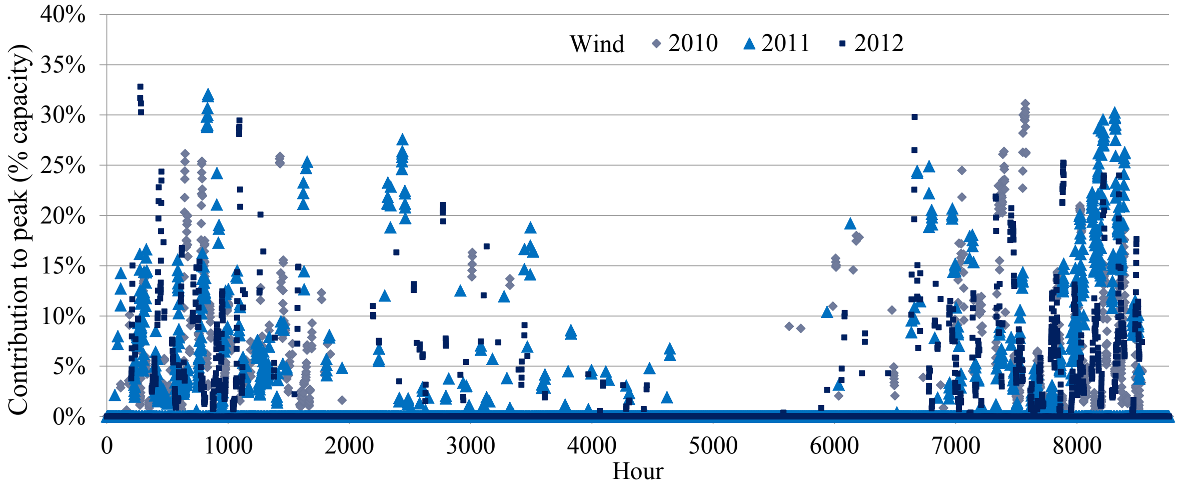

Figure 34: German wind contribution to peak demand 2010 to 2012

Solar generation contributes to peak demand for 25% in summer times. During April and June, the contribution is higher than observed for wind energy. Solar generates peak energy in the range of 0% to 10% during mid-January and mid-March as well as from November to December.

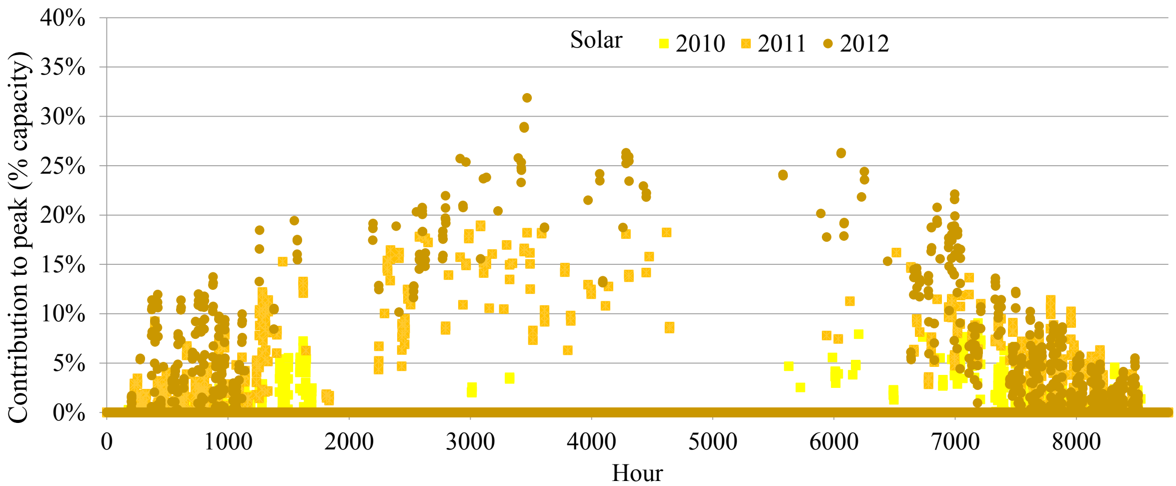

Figure 35: German solar contribution to peak demand 2010 to 2012

The duration curve of the contribution to peak demand shows that wind generates in all of the 876 hours, solar energy contributes only in about 600 hours. The maximum contribution of wind energy is 35% in all three-years; solar energy reaches this level in 2012. Figure 36 indicates that solar contribution increases continuously from 2010 to 2012 but wind contribution decreased in this timeframe.

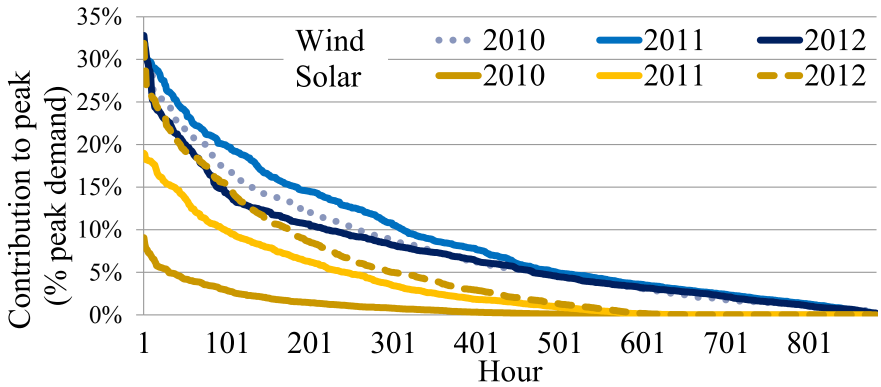

Figure 36: Duration curve - German wind & solar contribution to peak demand

The mean of wind contribution to peak demand is 0.08. Solar contribution mean is recorded to be 0.03. Differing from the predictability error and the volatility mean, the contribution to peak demand mean is always higher than zero. The higher the mean the lower the capacity costs. Thus, it is important to note, that a high mean is negative correlated with system security and therefore preferred by investors. The standard deviation of wind is 0.07, compared to solar risk of 0.05.

The third hypothesis is formulated based on the evaluation of risk measured by the standard deviation:

H3: The optimal contribution to peak demand portfolio holds based on a lower solar standard deviation a higher share of solar compared to wind energy

Wind skeweness for 2010 to 2012 is 1.19, solar skewness for the same timeframe 2.20 which leads to an overestimation of risk. Thus, the impact of skewness on risk is neglected.

Excess kurtosis for wind 2010 to 2012 is 0.83, but solar kurtosis indicates the existence of fat tails with a value of 4.9. The examination of the 5% highest and lowest wind and solar values (expressed as the average of the sum of all 876 extremes) records a value of 0.134 for wind and for solar of 0.097 compared to the mean of 0.0797 and 0.032 (absolute deviation of 0.054 and 0.065). This results in a higher probability mass in the upside risk. Upside risk is preferred over downside risk by investors since it increases the contribution of peak demand. Figure 37 shows the contribution to peak demand in the highest and lowest 5% of the 2010 to 2012 dataset.

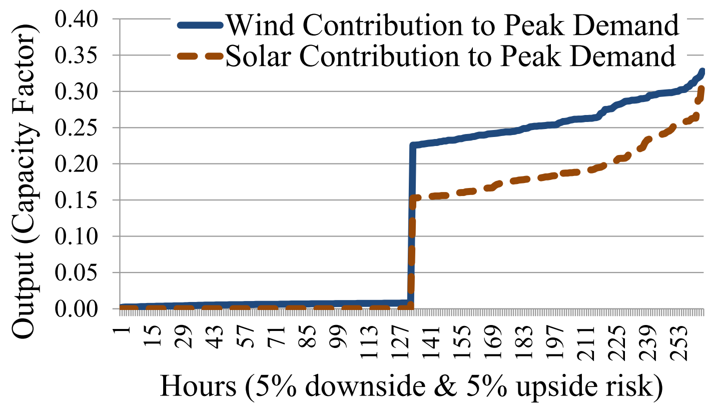

Figure 37: Tail analysis: contribution to peak demand ±5% extreme values

Testing for normality, the Jarque Bera test shows that the row data series does not fit a normal distribution (appendix (A)). So far, the 10% of peak demand distribution has not been focus of research. The times of peak demand is country specific. Clearly, the data outlined in figure 38a), b) is the foundation for a German case study, only.

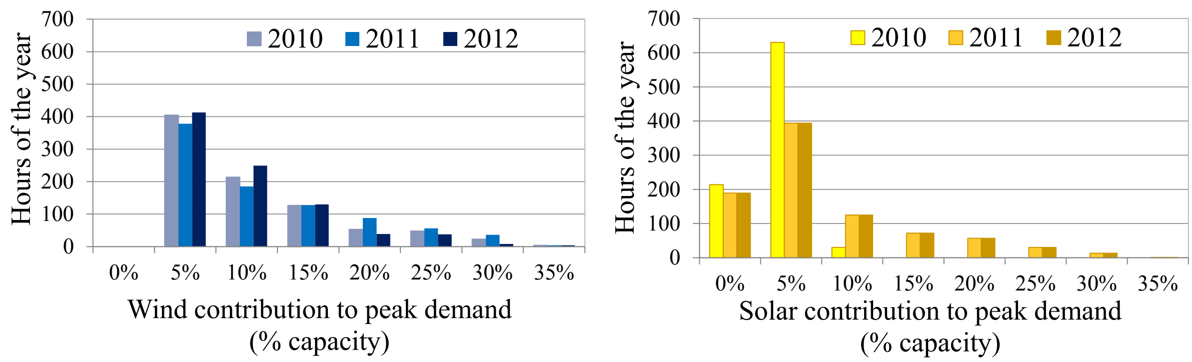

Figure 38a), b): Wind and solar contribution to peak demand distribution 2010 to 2012

The analysis indicates that wind and solar generation contribute each with around 400 hours to 5% of peak demand. However, the contribution of 15% to peak is more often (50 hours) provided by wind power.

To sum up, three interesting results are assessed. First, wind energy contributes to all hours of peak demand in times of high contribution up to 35%. Solar contributes in about 600 hours highest in summer with up to 35%. Second, a lower solar standard deviation is likely to overbalance solar in the contribution to peak demand portfolio. Third, extreme values for wind and solar are comprised in the tails. Both technologies show a higher probability mass in the upside risk. The histograms outlined in figure 38a), b) are the foundation to generate wind and solar portfolios that maximize the contribution to peak demand and minimize the variability during these hours. This dissertation assumes these distributions to be normal.

4.1.4. German dataset of political and investor measures

4.1.4.1. Wind and solar generation data 2010 to 2012

As figure 39 illustrates, the capacity factor of wind generation differs from hour to hour, month to month and year to year. The visual examination shows that the capacity factor of wind can reach up to 80% in winter times. Low wind generation is observed in Q2 of each year.

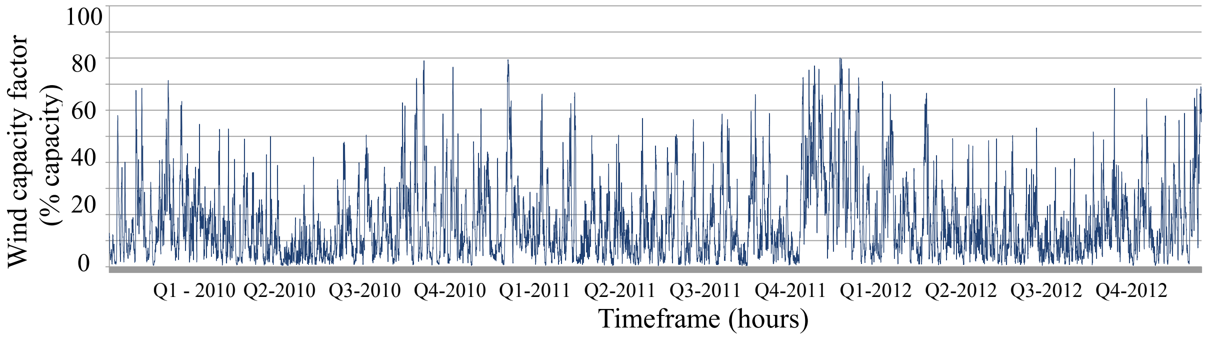

Figure 39: German wind hourly capacity factor 2010 to 2012

Wind generation installation rates increase from 27,209 MW in 2010 to 30,001 MW in 2012 resulting in a total output of 45,195 GWh in 2012. The minimal and maximal capacity factor varies from 0.4% to 80%. The average capacity factor in 2010, 2011 and 2012 is recorded to be 15%, 18.1% and 17.4%. Thus, the output decreases relatively to the installed capacity from 2011 to 2012. Table 4 represents generation output, installed capacity, mean-, median-, maximum-, and minimum capacity factor for wind and solar energy for the years 2010 to 2012.

	2010	**2011**	**2012**		**2010**	**2011**	**2012**
	Wind Generation				**Solar Generation**		
Generation output [GWh]	35,815	45,637	45,195		9,574	18,547	27,914
Installed capacity [MW]	27,209	28,739	30,001		16,536	21,896	29,702
Mean capacity factor (%)	15.0	18.1	17.4		6.6	9.7	11.0
Median capacity factor (%)	10.8	12.8	13.0		0.1	0.3	0.4
Maximum capacity factor (%)	79.0	79.3	80.1		52.2	59.8	74.6
Minimum capacity factor (%)	0.4	0.3	0.4		0.0	0.0	0.0

Table 4: Historical wind and solar generation data 2010 to 2012

Solar generation increases from 16,536 MW to 29,702 MW exceeding wind generation in 2012, although the installed capacity of wind and solar power is equal in 2012. Based on lower operating hours, solar energy output is only 62% of wind output. The mean capacity factor increased from 6.6% to 11%.

As shown in figure 40 the variance of the solar capacity factor ranges between 0% and 75%. Although this range is equal to the range of wind energy (0% to 80%) half of the values for solar are below 0.1, 0.3 and 0.4 (2010 to 2012) compared to half of the wind values recorded to be lower than 10.8 in 2010, 12.8 in 2011 and 13.0 in 2012.

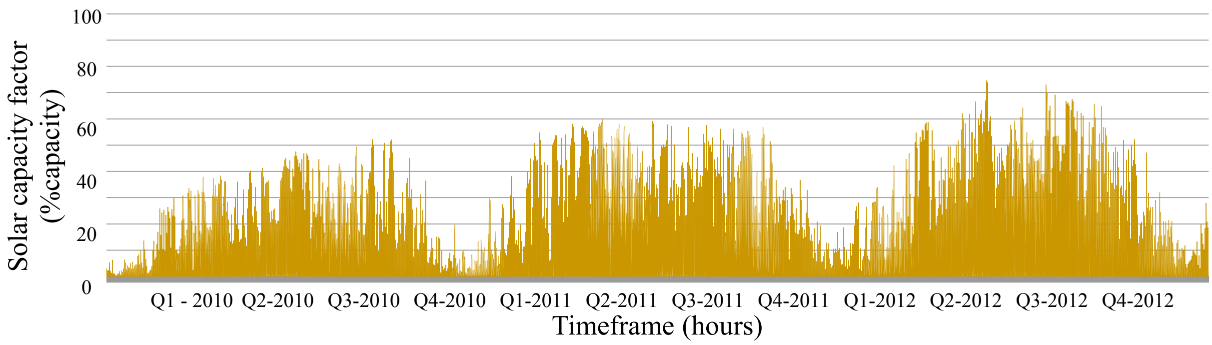

Figure 40: German solar hourly capacity factor 2010 to 2012

The next figure investigates the hourly duration curves of wind and solar generation. All three wind duration curves show equal characteristics but the 2010 solar duration curve differs from the 2011 and 2012 solar duration curves. The analysis shows that wind generates throughout the year (8,760h) but solar generation varies from 5,028 to 4,951 to 4,995 hours in the observed timeframe.

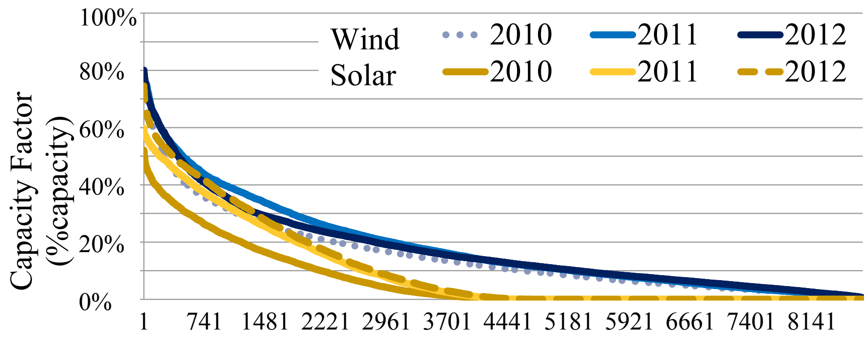

Figure 41: Duration curve - German wind and solar hourly capacity factor

Wind and solar generation show seasonal and diurnal differences. The average hourly wind generation in Q1 and Q4 is outlined in figure 42a) and ranges from 16% to 26%. The average mean capacity factor in Q1/Q4 is 123%, 119% and 126% above the annual mean of 2010, 2011 and 2012. During night times the highest wind capacity factor is recorded between hour 20 and 24. The mean capacity factor of the seasonal pattern in Q2 and Q3 illustrated in figure 42b) are compared to the annual wind mean capacity factor only 78% (2010), 82% (2011) and 74% (2012). The highest capacity factors within a year are identified in Q1/Q4 in hour 12 to 17.

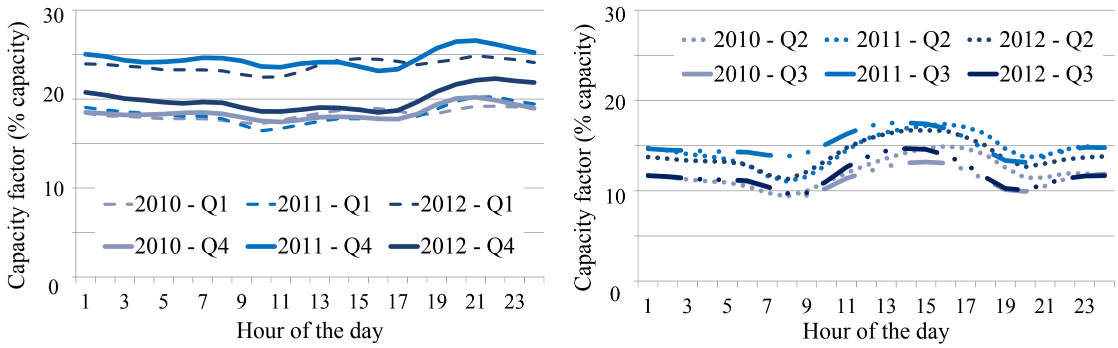

Figure 42a), b): Seasonal hourly wind capacity factor 2010 to 2012

As for wind generation, there are seasonal and especially diurnal patterns for solar generation. The solar mean capacity factor in Q1/Q4 is 50%, 57% and 49%, for Q2/Q3 152%, 142% and 145% of the annual mean capacity factor 2010 to 2012. In essence, the seasonal difference of solar generation is higher than for wind energy. The same is observed for the difference within a day ranging from 0% to 24% in Q1/Q4 (figure 43a) and from 0% to 48% in Q2/Q3 (figure 43b). Solar variation is compared to wind between Q1/Q4 and Q2/Q3 twice as high.

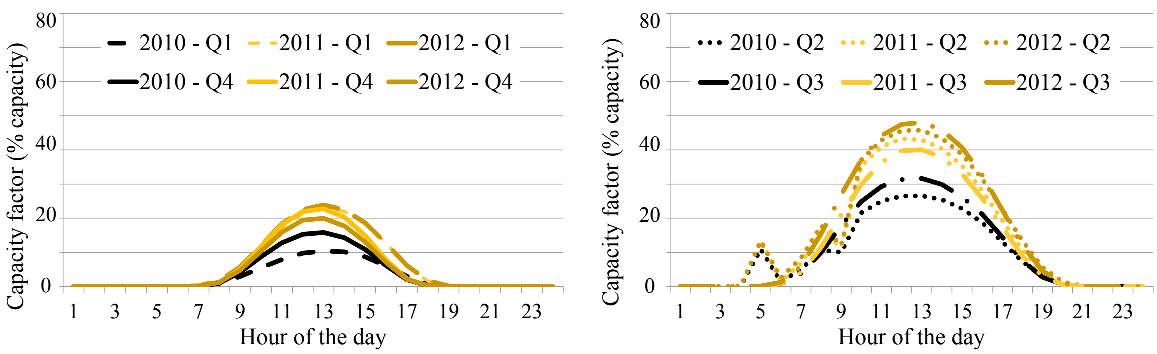

Figure 43a), b): Seasonal hourly solar capacity factor 2010 to 2012

As for the contribution to peak demand, the mean can only be positive. The higher the mean the higher the output per installed capacity. In this context, the wind mean capacity factor (2010 to 2012) is 0.17. The solar mean capacity factor is about half the value of wind recorded to be 0.09. The standard deviation of wind (0.15) is slightly higher than that of solar (0.14). To compute optimized levelized cost of energy portfolios in Chapter 4, the dataset is multiplied by inverse levelized cost of energy. Under the assumption that solar generation costs are at least as high as wind generation costs the fourth research question is formulated as:

H4: The optimal LCOE portfolio holds based on a lower solar standard deviation a higher share of solar energy compared to wind as long as the solar LCOE is below or equal to the wind LCOE

The skewness of wind generation of the total dataset of 26,280 consecutive points is 1.44 for 2010 to 2012. Therefore, risk is overestimated by supposing a normal distribution. The same applies to solar skewness recording a value of 1.69.

Surprisingly, excess kurtosis of wind and solar is equal with a value of 1.97 and indicates that extreme events are underestimated. The 5% extreme value analysis is performed for the highest and lowest 132 values for the dataset of 2,630 data points (±5%). The calculated values of 0.054 and 0.065 show a higher probability mass in the upside risk (wind: 0.134 compared to the mean of 0.079 and solar: 0.032 compared to the mean of 0.032). Upside risk is preferred over downside risk since it results in higher output. Figure 44 outlines ±5% extreme values for wind and solar generation.

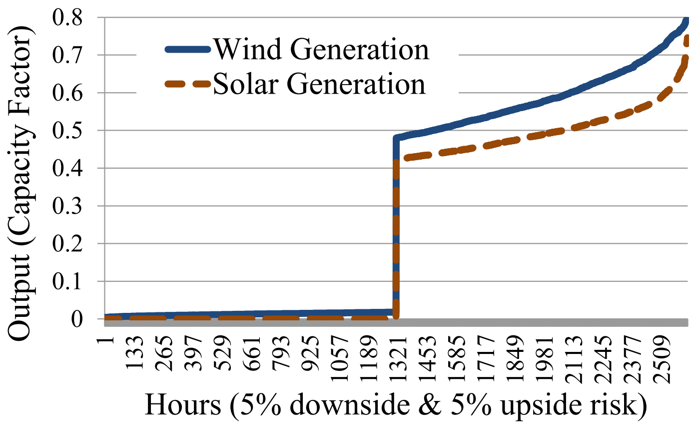

Figure 44: Tail analysis: generation ±5% extreme values

The Jarque Bera test rejects normality for all row data (appendix (A)). The probability distributions for wind and solar energy are plotted in the next graphs: figure 45a) and 46a) show the total range of wind and solar generation.

Figure 45b) and 46b) illustrate the generation between 0% to 20% of installed capacity. The visual observation of wind is in line with other studies and finds that wind generation is not equal to a normal distribution (Morgan, 1995; Garcia et al., 1998).

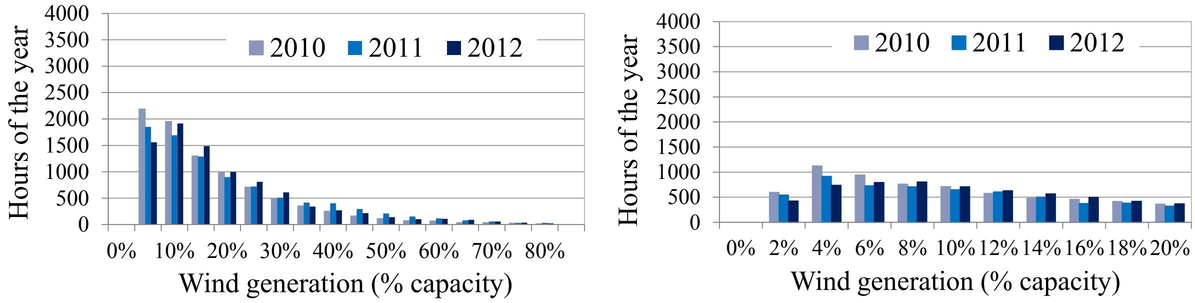

Figure 45a), b): Wind generation distribution 2010 to 2012

Although these distributions vary from the normal distribution most prior research discussed in Chapter 3 assumes a normal distribution for generation data. Nevertheless, there are other approaches to rebuilt wind generation patterns. Some may argue that the Weibull distribution (Morgan et al., 2011) is a widely accepted distribution for wind power generation. However, scientists find that the Weibull distribution is not able to represent all wind regimes such as e.g. times of zero wind speed or bimodal distributions. The approach of assuming a Weibull distribution appears not to be generally justified (Carta et al., 2009).

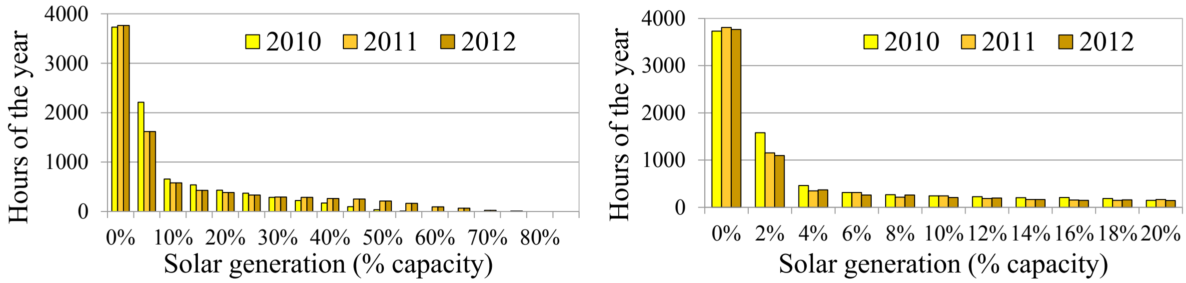

Figure 46a), b): Solar generation distribution 2010 to 2012

Only very few studies discuss the distribution of solar power. One study smooth solar data by a beta probability distribution for daily sunshine duration (Ettoumi et al., 2002). Another study discusses radiative transfer models and decomposition models. They find that modeling seasonal dependency corresponds with the performance of an annual modeling approach (Lopez et al., 2000). Nevertheless, the discussion is very limited and does not lead to a common understanding of wind and solar generation distributions.

The findings can be summarized as follows: first, both technologies show a variation of seasonal and diurnal generation pattern but the range of the capacity factor of solar generation is twice as high on a seasonal and five times as high on a diurnal timeframe compared to wind generation. Second, under the assumption of a normal distribution the skewness overestimates risk for all data series and third, extreme values in the tails indicate probability mass in the upside risk. The distributions outlined in figure 45a), 46a) are assumed to be normally distributed and used to calculate optimized political and investor portfolios described in the next section.

4.1.4.2. Wind and solar levelized cost of energy 2012, 2020 and 2050

As stated before, the generation data distribution is the foundation to switch from the technological to the financial perspective. The concept of levelized cost of energy (LCOE) for wind and solar power has found some applications since two decades. To identify reliable values, the literature review is limited to studies that have been published between 2009 and 2012. This timeframe is selected since wind and solar generation prices have gone through an extreme price decrease in this period. Wind turbine costs e.g. fell about one quarter from 970 to 687 Euro/kW from 2010 to 2012. Solar module prices dropped in the same timeframe by 60% (IRENA, 2013). Three major resources are used for literature review: first, reports published at wind and solar integration conferences in Europe from 2009 to 2012; second, literature research on the science direct database searching for LCOE, wind and solar; third, databases of German institutions that specialize in wind and solar cost development. International values are used to benchmark German data before this dissertation derives the parameters for different scenarios.

The results of the literature review show that most of the publications discuss wind LCOE. Table 5 summarizes the findings for wind LCOE calculations including time point and period, investment costs and financing parameters used by other scientists.

	NREL, 2009*	**Wiser & Bolinger, 2010**	**Boccard, 2010**	**Delucchi & Jacobson, 2011**	**Fraunhofer, 2012**
Year	2009	2008	2007	2007/2008/2020	2011
Capacity factor (%)	22/34/48	35/45	-	46/38/46	13 to 26
Country	US	US	ES, P, DE	Global	DE
Lifetime (years)		-		20/30/30	20
Financing period (years)	12/15/17	-	-	-	20
Equity (%)	-	-	-	-	30
Real discount rate (%)	4.2/5.8/13	-	7.5	10.4/10.4/10.3	9
Inflation (%)	-	-	-	-	-
Interest rate (%)	-	-	-	-	7
Investment Costs (€/kW)	956/1,318/2,004	847 to 1,465	-	1,480/1,272/880	1,000/1,200/ 1,400
O&M Costs**					
(€/MWh) [a]	13.1/4/2.3	8.47	-	-	15
(€/kW/year)[a]	-	-	-	23.32	-
(% of invest)[b]	≈ 1.3/0.4/0.23		2	≈ 1.5 to 2.0	≈ 1.5
LCOE (€/MWh)	42.4/47/55.5	34.68 to 46.24	63.1/66.8/74.3	43.2/43.2/23	60/70/110

Table 5: Wind LCOE publications 2009 to 2012

Notes for table 5: Dollars are converted to Euros with an exchange rate of 1.2974. *NREL uses a finance structure varying the IRR of a project. **O&M costs are either expressed in Euro/MWh or Euro/kW. [a]Maddaloni et al., (2009) found O&M costs of 23.43 Euro/kW for wind installations in Vancouver (converted with an exchange rate of 1.3388). For comparison, all values are converted to O&M costs in % of total investment. [b]EIA (2009) indicate a value of 1.5% O&M costs of total investment for wind in the US.

The wind analysis shows that the lifetime of wind is assumed to be 20 to 30 years with a capacity factor ranging from 15% to 48%. The financing period in Germany is determined to be 20 years with equity assumption of 30% and a real discount rate of 4% to 10%. All studies disregard inflation. The debt rate in Germany is found to be fairly high with 4.5% compared to other countries. Wind power investment costs range between 847 Euro/kW to 2,004 Euro/kW, indicating an average of 1,256 Euro/kWh. Operation and maintenance (O&M) costs can be expressed either in Euro/MWh, Euro/kW per year or as % of total investment. O&M costs in Euro/MWh vary from 2.3 up to 15. This implies on the one hand that there might be potential for improvement but on the other hand, the risk of high variations. On the contrary, prior research indicates a few ranges of O&M costs expressed as % of total investment of 1.5% to 2%.

Differing from wind energy, the lifetime for solar is expected to be slightly higher with 25 to 30 years. The real discount rates are equal to wind but the debt rate for solar is lower with 4.5%. Investment costs range significantly from 1,500 to 4,653 Euro/kWh due to different country specific learning curves in the last decades. In Germany, which is one of the leaders in installing solar systems, prices have fallen significantly in the last year. There is little research about solar O&M costs. Values are found to range between 9 Euro/kW and 30 Euro/kW. Solar LCOE variables are outlined in table 6.

	Delucchi & Jacobson, 2011	**Fraunhofer, 2012**
Year	2007/2008/2020	2011
Capacity factor	21/21/21	10
Country	Global	DE
Lifetime (years)	20/30/30	25
Financing period (years)	-	20
Equity (%)	-	20
Real discount rate (%)	10.4/10.4/10.3	7.5
Inflation (%)	-	-
Interest rate (%)	-	4.5
Investment Costs* (€/kW)	4,653/2,084/2,947	1,500/1,700/2,200
O&M Costs		
(€/MWh)	-	-
(€/kW/year)	9.00	30.00
(% of invest)	≈ 0.75%	≈ 2.5%
LCOE (€/MWh)	432/432/230	110/140/160

Table 6: Solar LCOE publications 2009 to 2012

Notes for table 6: Dollars are converted to Euros with an exchange rate of 1.2974. IRENA (2013) reported German investment costs of 1,696 Euro/kW. LCOE are not outlined in this study for Germany.

So far, wind and solar levelized cost of energy approaches include investment and O&M costs, but lack to integrate environmental savings related to fuel, decommission and waste. To properly assess the economics of wind and solar energy, one should include such savings (Jansen et al., 2006; Krey & Zweifel, 2006). The argument seems particularly appealing when comparing wind or solar to conventional generation. However, when comparing wind and solar only environmental savings (CO_2, decommission, waste) can be neglected since both technologies do not emit CO_2 or produce waste. Although the awareness that wind and solar power are linked to additional balancing and capacity costs, the levelized cost of energy concept has not been broadened by integrating system security costs, so far. As discussed in Chapter 2.1 and 2.2., these costs are of relevance for the energy system, especially at high wind and solar penetration levels. Therefore, this dissertation includes balancing and capacity costs in the analysis as illustrated in the integrated research framework (figure 15).

The definition of balancing costs varies among researchers. Gross et al. (2006) define balancing costs as costs that are caused by unpredicted variations as well as costs associated with the variation of demand compared to fluctuating output and the availability of reserve capabilities. In other words, costs of predictability errors and costs of variability are included in this definition. Balancing costs are assessed by the additional reserves needed when adding wind and solar to an energy system. They are country-specific and depend on the penetration of renewable energies, the degree of flexibility within a system, regulatory and operational differences. The definition of balancing by IEA (2011) relates to wind forecast, market structure and curtailment policy. The study states that balancing costs significantly depend on the availability of system flexibility. The more flexibility exists within an energy system, the lower the costs for additional generators providing balancing.

By implication and by comparing the values observed for the first and the second definition of balancing, both definitions are similar. Table 7 outlines the identified studies and balancing costs at different wind penetration levels.

Balancing costs (€/MWh) Wind penetration level	**10%**	**20%**	**30%**	**45%**
Milborrow, 2001 (US)	2.89	-	-	3.7
Ilex and Strbac, 2002 (UK)	-	3.01	3.24	-
MacDonald, 2003 (UK)	-	2.31	-	-
Dale et al., 2003 (UK)	-	3.12	-	-
Gross et al., 2006 (UK)	-	2.89	-	-
Skea et al., 2008 (UK)	-	2.31-3.47	-	-
IEA, 2011 (US)	2.54	2.54	3.85	-
IEA, 2011 (Schweden)	0.61	0.77	-	-
IEA, 2011 (Finland)	2.16	3.08	-	-
IEA, 2011 (DE)	2.46	-	-	-
Average balancing cost (€/MWh)	2.13	2.61	3.55	3.7

Table 7: Balancing costs 2001 to 2011

The average balancing costs in Euro/MWh including predictability errors and volatility costs are 2.13 for 15% penetration, 2.61 for 20% penetration, 3.55 for 30% penetration and 3.7% for 45% penetration. The values state that the higher the penetration level the higher the balancing costs.

Besides the definition of Gross et al. (2006) and IEA (2011), Katzenstein & Apt (2012) contribute by a research paper that discusses variability costs. They focus on mid-term balancing caused by variability and exclude costs related to predictability. Their optimization model provides ancillary services including load following and regulation in times of wind variability. The analysis is carried out for 20 locations in the US in the years 2008 and 2009 (calculated for three different capacity factors). Variability costs are defined in relation to wind capacity factors. Table 8 shows the results and states that most often an increase of capacity factor results in a decrease of variability costs.

Variability Costs (€/MWh) Capacity factor	**30%**	**35%**	**45%**
Katzenstein & Apt, 2012 (US)			
Year 2008	9.26	8.33	8.68
Year 2009	4.63	4.05	3.7
Average variability costs (€/MWh)	6.94	6.19	6.19

Table 8: Variability costs 2008 to 2009

Costs in 2008 are higher than in 2009 which is a result of lower ancillary services price levels in 2009 compared to 2008. Differing from expectations that variability costs are lower than balancing costs (since variability costs exclude costs related to unpredictability) the analysis shows that variability costs are higher at least in this research focusing on the US energy system. The average values are by far higher with 6.94 and 6.19 Euro/MWh for a wind penetration level of 30% and 35% to 45%. One may argue that the reliability of one publication that uses the variability method is not as high as balancing cost estimates of ten studies. With respect to this argument, this dissertation uses the average balancing costs outlined in table 7 for the following calculations.

To determine long-term costs related to capacity, two main methods to calculate capacity needs are found. The first method is an assessment of an overall change in system costs that arise from additional capacity requirements (Gross et al., 2006). This approach estimates the capacity needed to maintain the same level of system security while adding wind and solar power. One may challenge this view by arguing that this method decreases the operation hours of conventional power plants. Therefore, some researchers propose to link the costs of fluctuation to stand-by reserves instead. This stand-by generators operate in peak-times when wind and solar power are absent (Ilex & Strbac, 2002).

The second stream links costs to the back up or capacity reserve that would be required closing the gap between the capacity credit of wind or solar and the capacity credit of conventional power generators that would provide the same amount of energy. The capacity credit is a measure that outlines the amount of load that is provided by wind and solar with no increase in the loss-of-load probability of an energy system.

Both approaches are likely to generate the same findings since the system reliability costs of fluctuation are the fixed costs of energy-equivalent conventional plants (Gross et al., 2006). Table 9 illustrates the results of nine studies that calculate wind capacity costs. The average capacity costs are higher than the costs for balancing and range from 4.16 to 4.57 Euro/MWh for an increasing penetration level from 10% to 20%.

Capacity costs (€/MWh) Wind penetration level	**10%**	**20%**
Gross et al., 2006 (UK)	-	-
Capacity credit 20%	5.51	5.58
Capacity credit 30%	2.82	3.84
Ilex and Strbac, 2002 (UK)	-	3.01
MacDonald, 2003 (UK)	-	5.21
Dale et al., 2003 (UK)	-	4.51
Skea et al., 2008 (UK)	-	3.47-5.79
Boccard, 2010 (DE)	-	4.4
Boccard, 2010 (ES)	-	5.6
Boccard, 2010 (P)	-	4.1
Average capacity costs (€/MWh)	4.16	4.57

Table 9: Capacity costs 2006 to 2010

Neither balancing nor capacity cost studies discuss solar system security costs in detail. This dissertation assumes for the benchmark scenario that wind balancing and capacity costs are on an annual average basis equal to solar balancing and capacity costs. The cost increase is supposed to follow a linear trend line related to the total wind and solar penetration within the energy system. The assumptions of the benchmark scenario are drawn due to the lack of solar balancing and capacity data. Therefore, the resulting costs of wind and solar predictability, volatility and contribution to peak demand costs are treated in an equal way in this dissertation. However, the empirical research performed in this chapter showed that this is very likely to be not the case. The historical data showed that wind and solar cause different balancing or capacity needs. The determination of solar balancing and capacity costs are especially important for short- and mid-term costs. Furthermore, they are relevant to find ideal wind and solar portfolios in terms of levelized cost of energy. This dissertation uses sensitivities to examine the impact of varying wind and solar balancing and capacity costs. Nevertheless, the research gap of solar balancing and capacity costs at different penetration levels should be addressed and is further discussed in Chapter 5.

This dissertation derives from empirical studies the input parameters outlined in table 10 and defines three benchmark scenarios for the year 2012, 2020 and 2050. Financial and energy cash flows which are computed by using formula (13) to (18). Next, they are discounted to the real levelized cost of energy excluding inflation. Return is defined as the inverse real levelized cost of energy.

	Scenario 2012 (1 = real LCOE)		Scenario 2020 (2 = real LCOE)		Scenario 2050 (3 = real LCOE)	
	Solar	**Wind**	**Solar**	**Wind**	**Solar**	**Wind**
Penetration Level[a]	20	20	50	50	80	80
Capacity factor[b]	10	18	12	20	12	20
Lifetime (years)[c]	25	20	25	20	25	20
Degradation (% of year 1)	0.2		0.2		0.2	
Financing period (years)[d]	20	20	20	20	20	20
Equity (%)[e]	20	20	20	20	20	20
Real interest rate (%)[f]	7	9	6	9	6	9
Inflation (%)[g]	0	0	0	0	0	0
Debt rate (%)[h]	4.5	4.5	4.5	4.5	4.5	4.5
Investment Costs (€/kW)[i]	1500	1500	1000	1200	800	1000
O&M Costs (€/MWh)[j]	30	15	28	15	28	15
Balancing Costs (€/MWh)	2.61	2.61	3.95	3.95	4.50	4.50
Capacity Costs (€/MWh)	4.57	4.57	5.11	5.11	5.39	5.39
Real LCOE (€/MWh)	148.7	91.7	96.6	74.1	86.0	66.6
Real return (kWh/ct)[k]	0.067	0.109	0.104	0.135	0.116	0.150

Table 10: Wind and solar LCOE assumptions and results

Notes for table 10: [a]Penetration level is increased up to 80% of total energy generation in 2050. Based on the penetration level, balancing and capacity costs are derived. [b]Capacity factor for solar increased slightly over the years due to technological development e.g. tracker. The same applies to wind based on turbine optimization and higher hub heights. [c]Wind and solar lifetimes are derived from Fraunhofer (2012) values. [d]Financing period is 20 years. [e]Equity is based on expert interviews assumed to be 20% for wind and solar. [f]Real interest rates are assumed to slightly decrease due to technology saturation and lower risk over the defined time period. [g]Inflation is excluded to calculate the real LCOE and included for determining the nominal LCOE. [h]Solar and wind debt rate are derived from Fraunhofer (2012). [i]Investment costs are assumed to decrease for wind and solar. [j]O&M costs are expressed in Euro/MWh under the assumption that O&M costs are linked to the generated MWh and not to the installed kW. [k]Return is defined as the inverse of the LCOE.

Three findings are outlined for this section: first, levelized cost of energy decreases for wind and solar from 2012 to 2050. Second, wind LCOE in all years is lower than the solar LCOE. Third, balancing costs vary with the penetration level of wind and solar. For wind, they range from 2 to 4 Euro/MWh compared to wind capacity costs ranging from 4 to 5 Euro/MWh. It is assumed that solar balancing and capacity costs are equal for the benchmark scenario.

4.2. Portfolio development and testing of hypothesis

The mean-variance portfolio analysis calculated in this section depends on different objective functions defining variables to quantify return and risk. This dissertation defines based on literature research and practical experience four functions: maximizing predictability, minimizing volatility, maximizing contribution to peak demand and minimizing total system costs. Risk is in all calculations defined as the variability of the objective functions. Ideal portfolios for each function are defined as the portfolio with the lowest risk relative to its return since investors are assumed to be risk averse. The following sections are structured as follows:
First, the covariance and the correlation coefficient of wind and solar in the different years is calculated and outlined in detail in appendix (B). Second, the historical 2010 to 2012 efficient frontier is computed and used as a benchmark (26,280 consecutive data points). This efficient frontier enables to identify the optimal theoretical wind and solar portfolio for risk averse investors. Third, a sensibility analysis is performed.

4.2.1. Technological optimized portfolios

4.2.1.1. Optimal predictability error portfolios

The objective function in this section determines optimal portfolios (the share between wind and solar within a portfolio) that minimize predictability per installed unit of installed capacity. The function minimizes hourly variability of the forecast error. Thus, it aims to limit the need of short-term balancing when adding wind and solar to the energy system. Formula (8) and (9) are used to calculate the data series for the predictability error before calculating the covariance and the correlation coefficient with formula (1) and (2). The correlation coefficient of wind and solar data from 2010 to 2012 is negative related with -0.00147. Negative correlation indicates the existence of potential to reduce forecast error variability. Figure 47 shows the theoretical efficient frontier for wind and solar power portfolios for 2010 to 2012.

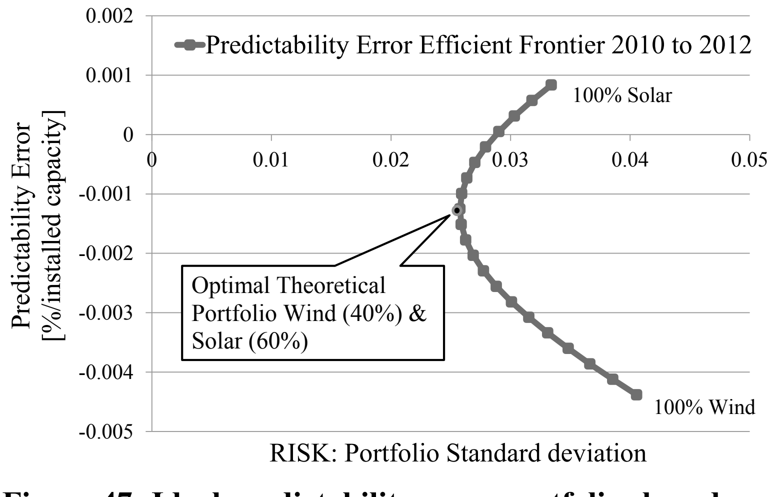

Figure 47: Ideal predictability error portfolios based on 26,280 data points

Timeframe: 2010 to 2012

The frontier is constructed by computing the minimal standard deviation (risk) for any given level of average predictability error (return). The optimization model illustrates the combinations that are possible when varying the proportion of wind and solar power.

The result of the optimization approach supports the postulated relationship between the standard deviation and the share within a portfolio. As expected, hypothesis 1 is supported resulting in an optimal theoretical wind and solar portfolio that consists of 40% wind and 60% solar. The mean of this portfolio is -0.00125, the standard deviation is 0.02577. This portfolio is likely to occur at a probability of 2σ within the range of -0.02702 and 0.02451 (appendix (D)).

4.2.1.2. Optimal volatility portfolios

In this section, optimal theoretical volatility portfolios are constructed. The data series is calculated with formula (10) and (11). More precisely, portfolios are computed by minimizing volatility and minimizing the variability of volatility. The goal is to reduce the need for mid-term balancing either in a positive or a negative way. After calculating the covariance and the correlation coefficient the 2010 to 2012 data indicates a low correlation between wind and solar of 0.097. This indicates potential for risk reduction. The volatility efficient frontier is illustrated in figure 48.

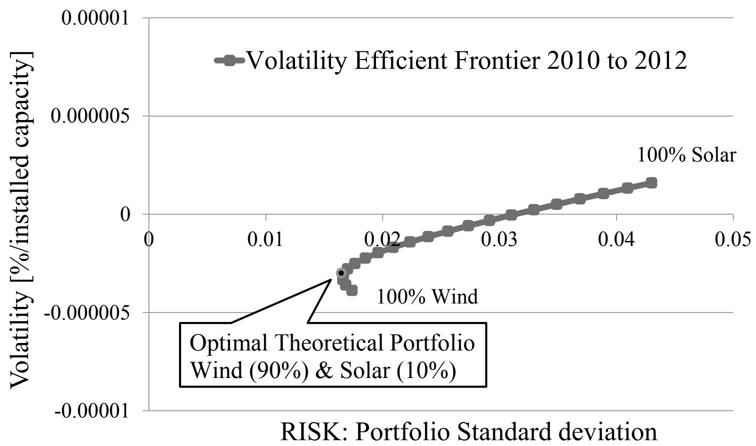

Figure 48: Ideal volatility portfolios based on 26,280 data points

Timeframe: 2010 to 2012

This optimization model tests hypothesis 2, assuming that the wind share is higher than the solar share. The result supports hypothesis 2 and determines that the optimal theoretical combination that minimizes risk holds 90% wind and 10% solar energy. The mean is -0.000003 with a standard deviation of 0.016. With a probability of 2σ the optimized portfolio ranges between -0.01660 and 0.01659.

4.2.1.3. Optimal contribution to peak demand portfolios

This section uses an objective function that computes for any level of contribution to peak demand the minimum standard deviation. The goal is to maximize for system reliability, especially in times of high demand levels. Using the correlation coefficient between wind and solar of -0.1082, this dissertation calculates based on formula (12) the dataset for the contribution to peak demand. The efficient frontier of 2010 to 2012 is constructed and plotted in figure 49.

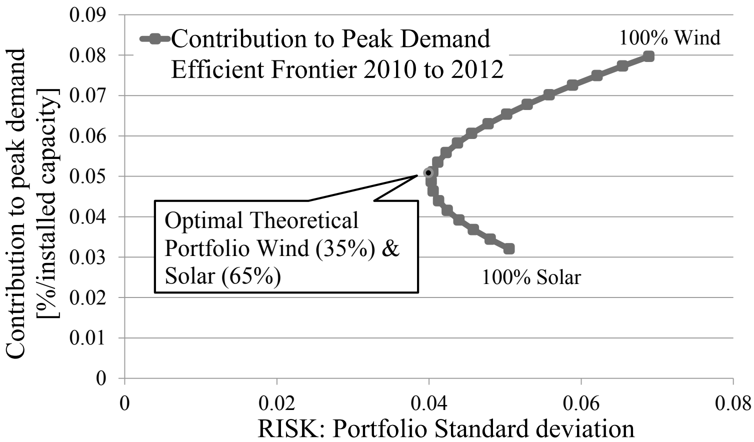

Figure 49: Ideal contribution to peak demand based on 26,280 data points

Timeframe: 2010 to 2012

Hypothesis 3, which assumes a higher share of solar in the portfolio is confirmed by the optimization model. The optimal theoretical wind and solar portfolio that minimizes risk consists of 35% wind and 65% solar energy. The mean is reported to be 0.04871 with a standard deviation of 0.04030. The results ranges from 0.00841 to 0.08901 within the probability of 2σ (appendix (D)).

4.2.2. Sensitivity analysis of technological optimized portfolios

This section assesses the sensitivity of the results. First, the timeframe of three-years which is the foundation for the analysis is reduced to one year data. For each year (2010, 2011 and 2012) optimal portfolios are constructed. In the second step, the historical German wind and solar portfolios that hold a wind share of 62% in 2010, 57% in 2011 and 50% in 2012 are compared to the efficient frontier of these years

4.2.2.1. Sensitivity analysis for predictability error portfolios

The analysis distinguishes between 2010, 2011 and 2012 and illustrates in figure 50 the three optimal theoretical efficient frontiers (EF). The calculations show that the optimal theoretical risk level of each year varies from lowest risk (0.022) to highest risk in 2010 (0.03). In all three-years, the optimal theoretical portfolio overestimates generation.

The optimal wind share ranges from 20% to 30% (2011) to 50% (2010). As expected, the results are sensitive to the selected timeframe. Longer timeframes level out extreme values that might occur in a single year. Table 11 outlines the optimal portfolio for 2010, 2011 and 2012.

Ideal Predictability Error Portfolios	Solar	Wind
Wind & Solar 2010	50%	50%
Wind & Solar 2011	70%	30%
Wind & Solar 2012	65%	35%

Table 11: Ideal predictability error portfolios for 2010, 2011, 2012

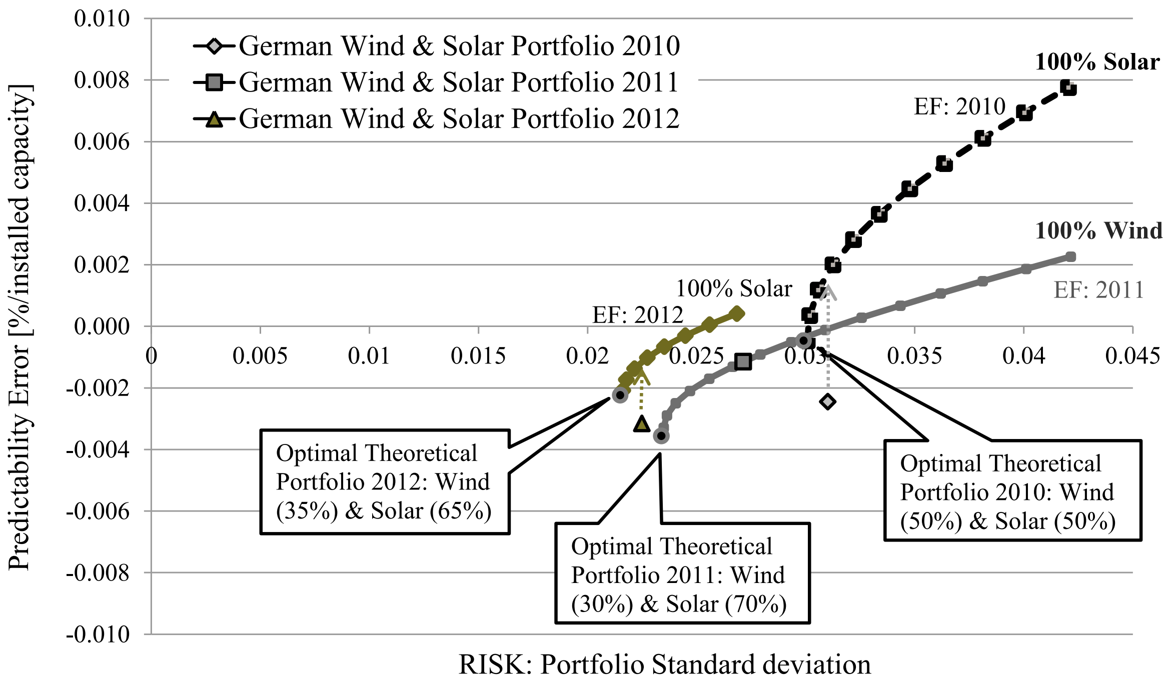

Figure 50: Ideal predictability error portfolios based on 8,760 data points

Timeframe: 2010, 2011 and 2012

Comparing the historical German wind and solar portfolios to the efficient frontiers of these years is evidence for potential improvements. At the same level of risk, a lower predictability error in 2010 (-0.0032 to -0.0018) and 2012 (-0.0022 to 0.0018) could have been achieved by increase the share of solar power from to 38% to 65% in 2010 and from 50% to 75% in 2012. The range of the results being in the 2σ spread shows that the range decreased from 2010 (-0.03 to 0.03) to 2012 (-0.024 to 0.019). The visual illustration is plotted in appendix (D).

4.2.2.2. Sensitivity analysis of volatility portfolios

The implications of the efficient frontiers (EF) constructed in figure 51 are straightforward: first, the range of risk level in the three-years is small (0.015 to 0.018). Second, the efficient frontier of 2010 shows positive volatility on the contrary to 2011 and 2012 identifying negative volatility. Third, the range within the three-years of optimal portfolios in 2010, 2011 and 2012 varies for only 10%. Differing from expectations, the three different annual datasets result in the same optimal portfolio. Thus, the selected timeframe for the ideal volatility portfolio seems not to be as sensitive to the results as e.g. the timeframes selected for predictability errors. Table 12 shows the optimal 2010, 2011 and 2012 portfolio.

Ideal Volatility Portfolios	**Solar**	**Wind**
Wind & Solar 2010	20%	80%
Wind & Solar 2011	10%	90%
Wind & Solar 2012	10%	90%

Table 12: Ideal volatility portfolios for 2010, 2011, 2012

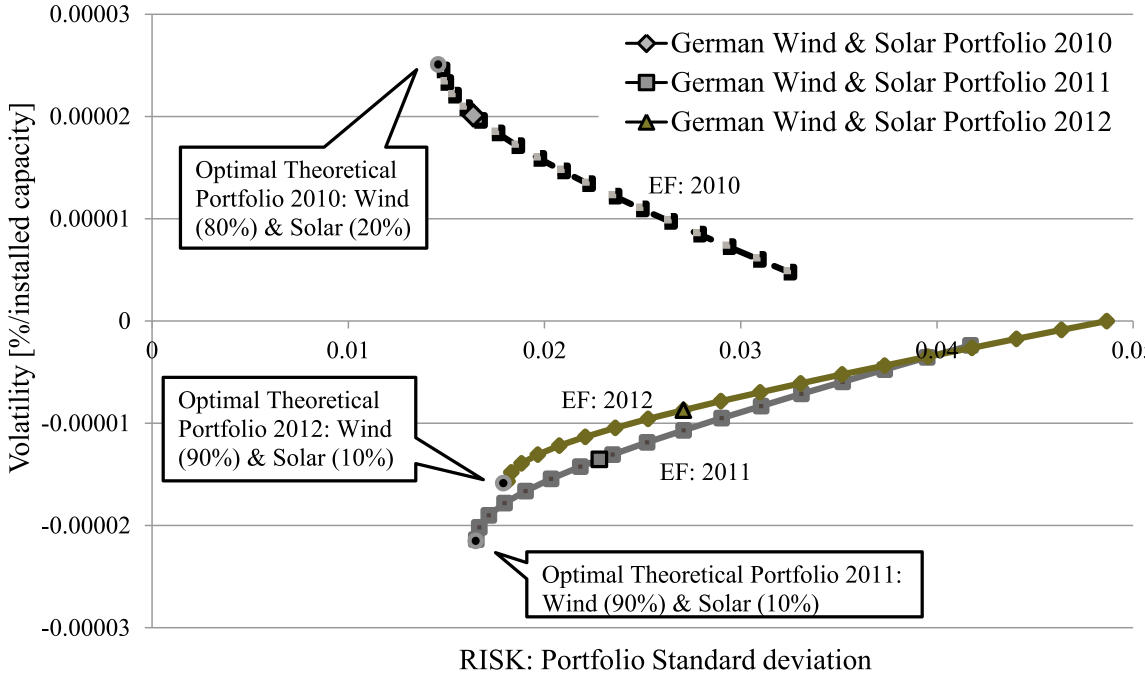

Figure 51: Ideal volatility portfolios based on 8,760 data points

Timeframe: 2010, 2011 and 2012

Surprisingly, all portfolios are on the efficient frontier. However, the risk level of the portfolios could have been decreased by adding wind energy to the portfolio. Risk in 2010 could have been decreased from 0.017 to 0.015, in 2011 from 0.023 to 0.016 and in 2012 from 0.028 to 0.018. The range of the results within 2σ is lower than found for predictability errors and increases slightly from -0.015 to 0.015 in 2012 to -0.019 to 0.019 in 2012 (appendix (D)).

4.2.2.3. Sensitivity analysis of contribution to peak demand portfolios

The sensitivity analysis of the contribution to peak demand implies three findings. First, the risk variation of the optimal theoretical portfolios is high ranging from 0.015 to 0.045. Second, it appears that there are high differences between the optimal portfolio in the three-years holding a wind share of 5% in 2010, 28% in 2011 and 53% in 2012. Lastly, the selected timeframe is sensitive to compute the optimal portfolio. Taking a longer timeframe (> 1 year) seems to enhance the reliability of the results. Table 13 illustrates the ideal 2010, 2011, 2012 portfolios.

Ideal Contribution To Peak Portfolios	Solar	Wind
Wind & Solar 2010	95%	5%
Wind & Solar 2011	72%	28%
Wind & Solar 2012	47%	53%

Table 13: Ideal contribution to peak demand portfolios for 2010, 2011, 2012

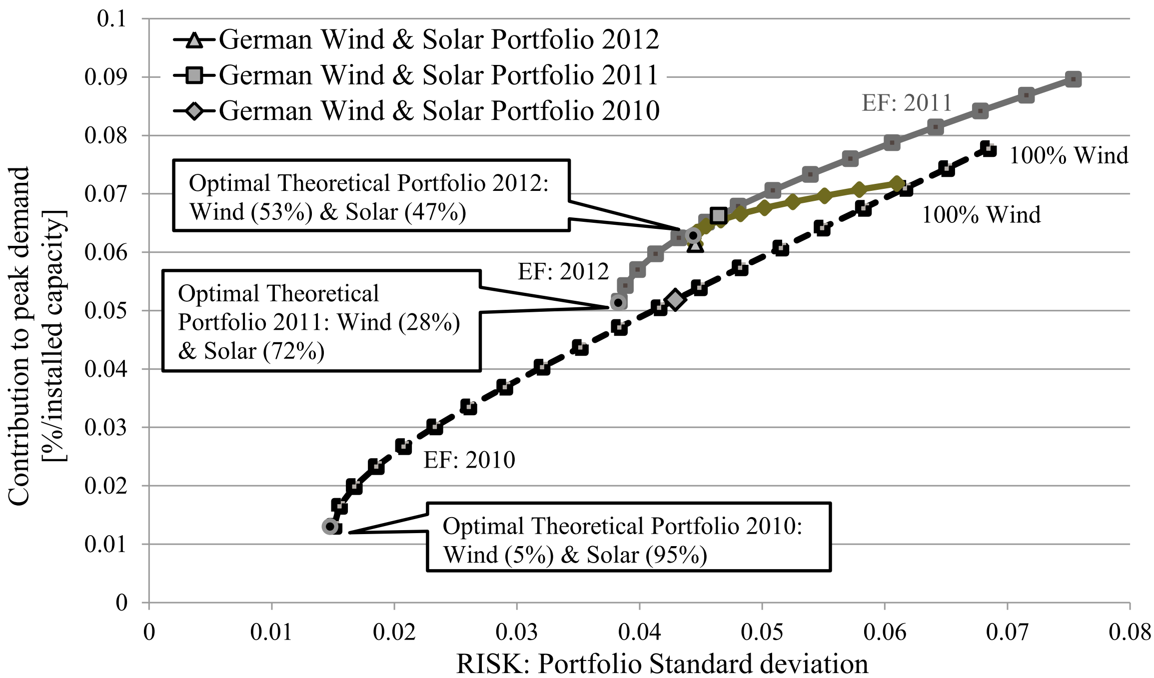

Figure 52: Ideal contribution to peak demand based on 8,760 data points

Timeframe: 2010, 2011 and 2012

The visual observation shows that the historical 2010, 2011 and 2012 portfolio lie on the efficient frontier. The actual 2012 portfolio is close to the optimal theoretical portfolio. Nevertheless, the risk of the 2010 and 2012 portfolio could have been decreased by adding solar to the portfolio resulting in a minimized standard deviation of 0.015 (compared to 0.043) and 0.039 (compared to 0.048). The results being in the 2σ range increases significantly over the years from 0.001 to 0.003 in 2010 to 0.019 to 0.108 in 2012 (appendix (D)).

4.2.3. Political and investor optimized portfolios

4.2.3.1. Optimal LCOE portfolios – real vs. nominal

This section differs from the previous ones in that it focuses on a financial measurement and defines the ideal portfolio to be the most cost efficient solution. The fourth objective function therefore aims to minimize total system costs and their variability. To assess optimal theoretical portfolios (OTP) the 2010 to 2012 data generation series is multiplied with the inverse real and nominal levelized cost of energy. The goal is to maximize the inverse levelized cost of energy to find the ideal portfolio from the political and investor perspective. The correlation coefficient of wind and solar is -0.1505 which indicates potential for risk reduction. The optimization model calculates in the first place the efficient frontier of 2012 for real (Scenario 1) and nominal (Scenario 1b) inverse levelized cost of energy displayed in figure 53. The real wind LCOE in 2012 is 91.7 Euro/MWh, the solar LCOE is 148.7 Euro/MWh. The nominal wind LCOE is higher with a value of 95.5 Euro/MWh and a solar value of 156.84 Euro/MWh.

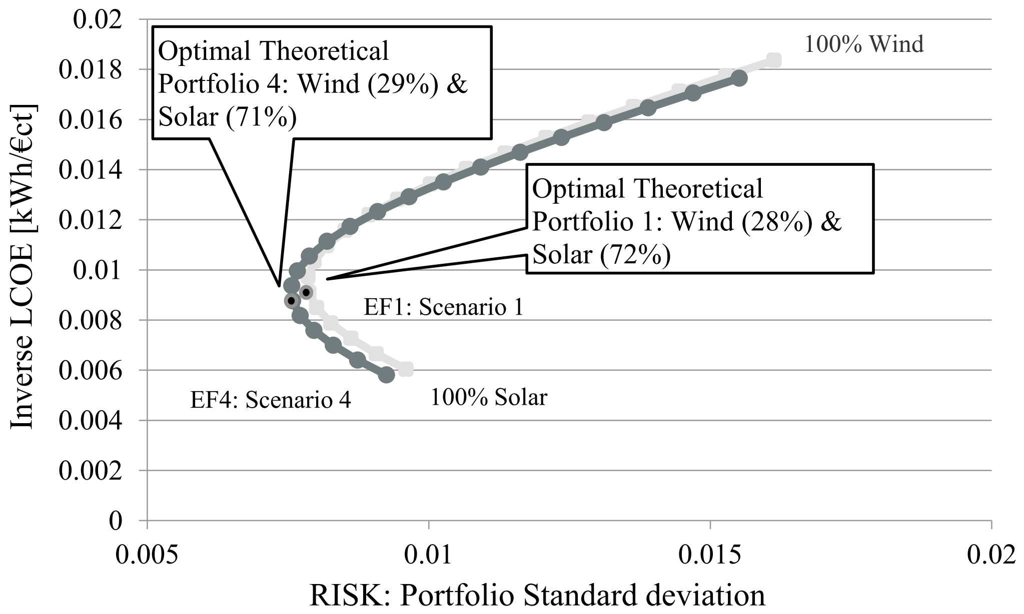

Figure 53: Ideal real and nominal LCOE portfolio based on 8,760 data points 2012

The findings supports hypothesis 4 which assumes a higher solar share in case solar LCOE is higher or equal to wind LCOE. The optimal theoretical real LCOE portfolio holds 28% wind, the nominal LCOE a slightly higher share of 32% wind. The analysis seems to indicate higher risk (0.0079 vs. 0.0075) for the real LCOE. The results are in the range of 2σ slightly lower for the real LCOE portfolio (0.0096 to 0.0175) than for the nominal LCOE portfolio (0.01405 to 0.0216). To reduce complexity, this dissertation limits further analysis to the real LCOE which calculates without inflation.

4.2.3.2. Optimal LCOE portfolios – real LCOE for 2012, 2020 and 2050

The discussion in this section focuses on identifying the optimal theoretical LCOE portfolios in the long-term. The LCOE forecast in section 4.1.3.3 is multiplied with the generation data series. The 2012 scenario (Scenario 1) has already been calculated in section 4.2.3.1. Optimal 2020 theoretical portfolios are constructed under the assumption of a wind LCOE of 74.1 Euro/MWh and a solar LCOE of 96.6 Euro/MWh (Scenario 2). Scenario 3 which computes ideal 2050 portfolios is developed by using a wind LCOE of 66.6 Euro/MWh and a solar LCOE of 86.0 Euro/MWh. Table 14 outlines the mean, the standard deviation of inverse wind and solar LCOE as well as the specific share of the optimal portfolios.

	Scenario 2012 (OTP 1 = real LCOE)		**Scenario 2020 (OTP 2 = real LCOE)**		**Scenario 2050 (OTP 3 = real LCOE)**	
	Solar	**Wind**	**Solar**	**Wind**	**Solar**	**Wind**
Mean	0.006	0.0184	0.009	0.023	0.010	0.025
Standard deviation	0.010	0.0161	0.015	0.020	0.016	0.022
Ideal portfolio	72%	28%	63%	37%	64%	36%

Table 14: Mean and standard deviation of Scenario 1, 2, 3s

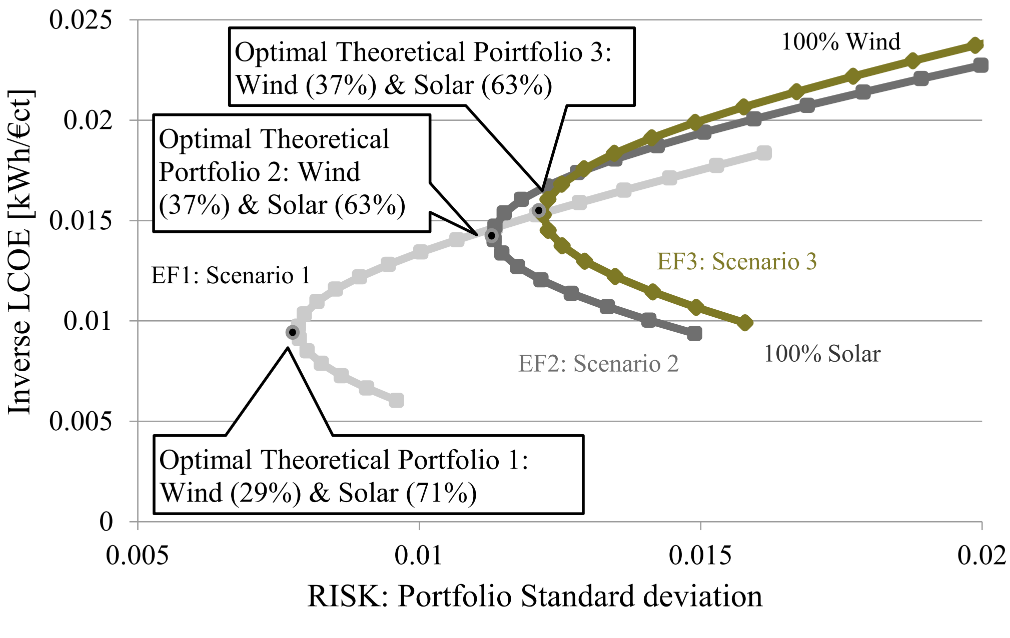

Figure 54: Ideal real LCOE portfolios based on 8,760 data points for 2012, 2020, 2050

Hypothesis 4 is supported for all three-years since within the ideal portfolio the solar share exceeds the wind share. The optimal portfolio share of wind grows over the years from 28% to 37% to 35%. The risk level increases from 0.008 to 0.0125 from 2010 to 2012. At the same time, potential returns increase from 0.01 to 0.015.

4.2.4. Sensitivity analysis of political and investor optimized portfolios

4.2.4.1. Sensitivity analysis for balancing and capacity costs for LCOE portfolios

The sensitivity analysis varies balancing and capacity costs for solar power. This is justified by the limited availability of literature investigating this topic (IEA, 2011). To determine balancing costs in the first step, solar generation is observed. This takes place during day times only, which limits required balancing needs to these hours. Therefore, solar is not assumed to cause higher balancing costs than wind. On the contrary, solar capacity costs are very likely to be higher than for wind since solar will not be able to provide capacity during night times. In addition to this, wind contributes twice as much as solar. Differing from the benchmark scenarios (Scenario 1-3), this sensitivity analysis expects solar capacity costs to be twice as high as wind capacity costs. Solar capacity costs are assumed to be 10.97 Euro/MWh for 2012, 13.93 Euro/MWh in 2020 and 16.87 Euro/MWh in 2050. These values are average costs over the timespan of one year. Costs in a specific hour might be higher or lower than outlined in figure 55.

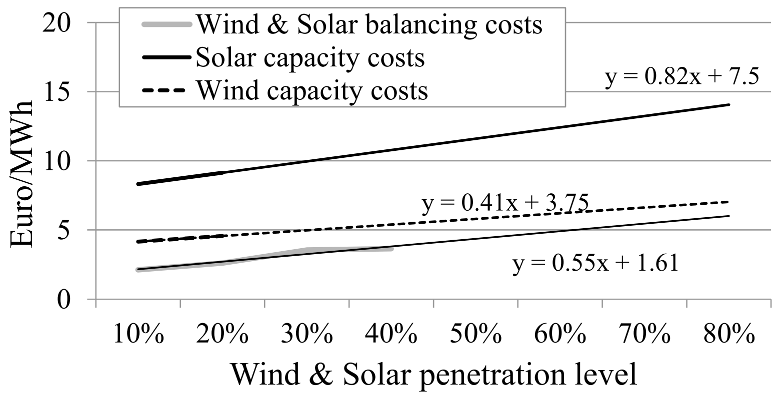

Figure 55: Wind and solar balancing and capacity costs

The input solar LCOE is 155.09 Euro/MWh in 2012, 105.98 Euro/MWh in 2020 and 97.45 Euro/MWh in 2050. The optimization model finds that higher solar capacity costs strengthen the support for hypothesis 4. The results are sensitive to balancing and capacity costs. Twice as high solar capacity costs result in a 5% lower wind share in 2020 and 2050 portfolio compared to Scenario 2 and 3.

	Scenario 4: 2012		**Scenario 5: 2020**		**Scenario 6: 2050**	
	Solar	**Wind**	**Solar**	**Wind**	**Solar**	**Wind**
Mean	0.006	0.0184	0.008	0.023	0.009	0.025
Standard deviation	0.009	0.0161	0.014	0.020	0.014	0.022
Ideal portfolio	72%	27%	67%	33%	66%	32%

Table 15: Mean and standard deviation of Scenario 4, 5 ,6

4.2.4.2. Sensitivity analysis for wind investment costs for LCOE portfolios

The following sensitivity analysis varies the installation costs per kW for wind. Installation costs are selected since their impact on levelized cost of energy is significant (Fraunhofer, 2012). Wind installation costs are assumed to be higher than in the benchmark scenario with 2,000 Euro/kW in 2012, 1,700 Euro/kW in 2020 and 1,500 Euro/kWh in 2050. The wind levelized cost of energy is 114.86 Euro/MWh in 2012, 94.96 Euro/MWh in 2020 and 87,45 Euro/MWh in 2050. The optimization model indicates that in all years the standard deviation decreases which leads to a higher share of wind within the portfolio. The share of wind is higher compared to the benchmark scenarios (OTP 1, OTP 2, OTP 3): 9% in 2012, 11% in 2020 and 11% in 2050. Nevertheless, this sensitivity analysis further supports hypothesis 4.

	Scenario 7: 2012		**Scenario 8: 2020**		**Scenario 9: 2050**	
	Solar	**Wind**	**Solar**	**Wind**	**Solar**	**Wind**
Mean	0.006	0.0147	0.008	0.019	0.010	0.019
Standard deviation	0.010	0.0129	0.013	0.015	0.016	0.017
Ideal portfolio	63%	37%	52%	48%	53%	47%

Table 16: Mean and standard deviation of Scenario 7, 8 ,9

The sensitivity analysis for solar balancing and capacity costs and the sensitivity analysis for wind installation costs show the same results as outlined in the empirical section 4.1.4.1. Multiplying the hourly data set with defined inverse levelized cost of energy changes the standard deviation of the solar and the wind data set and therefore results in different portfolios. In case the wind LCOE is higher (100%) than the solar LCOE (<100%), the share of wind within the portfolio increases. For instance, if the solar LCOE is 10% lower than the wind LCOE the standard deviation of wind is 7% lower than the solar standard deviation. This leads to a higher share of wind compared to the portfolio in which the LCOE of both technologies is equal. On the other hand, if the wind LCOE is lower (e.g. 80%) than the solar LCOE (e.g. 100%), the wind standard deviation is 29% higher than the solar standard deviation. Thus, solar power exceeds the wind share within the optimal portfolio.

Wind LCOE (%)	100	100	100	100	100	100	100	100	100	
Solar LCOE (%)	90	80	70	60	50	40	30	20	10	
Wind Stdv / Solar Stdv (%)	**-7**	**-17**	**-28**	**-38**	**-48**	**-59**	**-69**	**-79**	**-90**	
Wind LCOE (%)	100	90	80	70	60	50	40	30	20	10
Solar LCOE (%)	100	100	100	100	100	100	100	100	100	100
Wind Stdv / Solar Stdv (%)	**3**	**15**	**29**	**48**	**72**	**107**	**158**	**244**	**417**	**933**

Table 17: Wind standard deviation in % compared to solar standard deviation

4.2.5. Technological, political and investor optimized portfolio

This section discusses the integration of the optimal portfolio from a technological, political and investor perspective. The model used in section 4.2.1. optimized portfolios from a technological perspective (namely, predictability error, volatility, contribution to peak demand) to hold a share of 35%, 90% and 40% wind, respectively. Looking at the levelized cost of energy efficient frontier plotted in figure 56, one may conclude there is no optimal solution from the technological perspective based on the argument that the three different optimized portfolios lie on different points on the frontier. The ideal technological predictability portfolio overweighs solar energy based on the lower standard deviation of 0.0011. The lower standard deviation is related to a better predictability especially during night times in which forecast and actual generation are equal. Extremes within a large portfolio can be observed only very few times compared to wind. The optimal theoretical volatility portfolio identifies a portfolio that holds a small share of solar. The high solar standard deviation of 0.043 outlines that the volatility defined as the generation difference from one to the next hours is higher than for wind. For solar generation, this occurs almost every hour from night to day generation (hourly increase) and from day to night generation (hourly decrease). Additionally, solar energy generation shows two extremes: the highest generation during noon hour and the zero generation during night times. Although the generation of wind energy varies, the degree to which it hourly differs in the observed timeframe is by far lower than for solar.

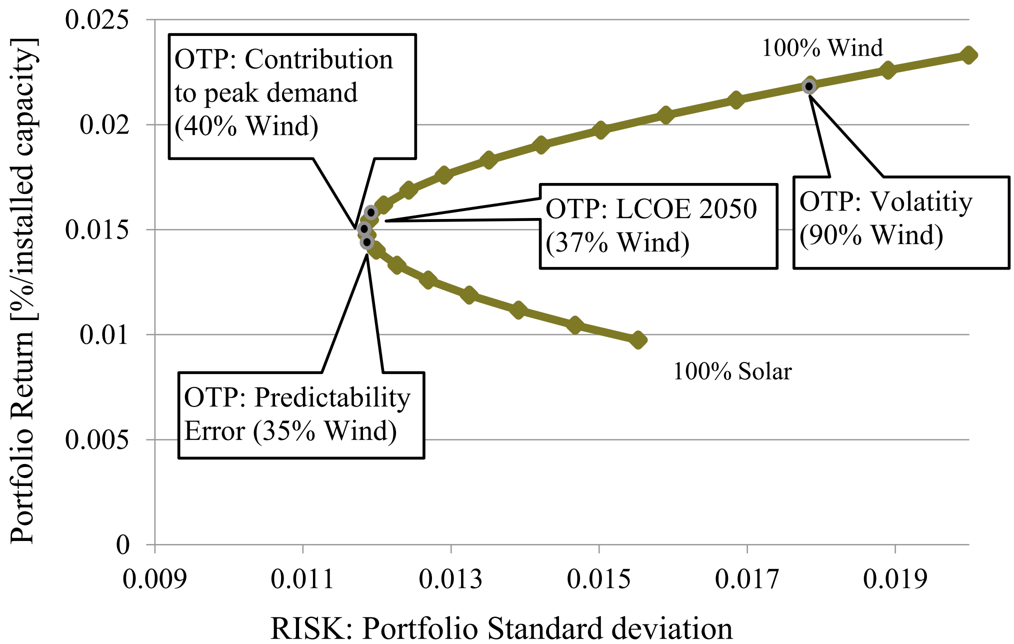

Figure 56: Ideal LCOE 2050 efficient frontier based on 26,280 data points (2010 to 2012)

The ideal contribution of peak demand portfolio outlines that although solar contributes less kilowatt-hours it contributes on a more constant basis (solar standard deviation of 0.05). Less extremes of solar contribution are observed. The LCOE theoretical optimized portfolio identifies a portfolio in that solar overweighs wind energy. Solar energy including balancing and capacity costs is assumed to be more expensive than wind energy. This results in a lower solar standard deviation (table 17). Surprisingly, as outlined above two out of three optimized technological portfolios (predictability, contribution to peak demand) propose a wind share of 35% to 40%. Furthermore, the analysis finds that the long-term optimized political and investor LCOE portfolio in 2050 lies within this range and suggests a share of 37% wind energy.

On the contrary, the portfolio that minimizes volatility differs significantly from the others and recommends a composition of 90% wind and 10% solar energy with the underlying assumption of volatility being commonly defined as the difference from one to the next hour. One may now argue in two ways: first, volatility should not be related to consecutive hours but related to the variation of the load. This said, only hours in which the volatile generation changes from one to the next hour in the opposite direction compared to the load are countable hours of volatility. Therefore, in case the load and the generation both increase in one hour, this hour would not count to the hours of volatility. On the other hand, if the load decreases and the generation increases or vice versa the hour would count as volatility. Computing volatility defined related to load shows that the optimal portfolio still holds a share of 65% wind.
Second, one may outline that hours of zero solar generation (nighttime) should not be included into the analysis since these hours are not volatile. Nevertheless, the question of the timeframe which should be excluded can be raised since solar energy starts to generate during summer times around 5am and during winter times around 7am. Others may argue that excluding night hours of solar energy leads to a different solar data set and should not be compared to a 24-hours wind data set. In addition to this, the advantage that solar energy is not volatile during night hours would not be valued. Calculating the optimal volatility portfolio by using a historical data set that excludes night hours (7pm to 6am) shows that the results do not vary compared to the analysis including night hours.

The three technological portfolios are not evaluated on a financial basis. Thus, it is assumed that the higher the predictability error and volatility the higher the likeliness of additional balancing costs. Furthermore, the higher the contribution to peak demand the lower the likeliness of additional cost. The question if this is the case in a real market is not addressed in this dissertation and should be matter to further research.

It appears that a portfolio that holds a share of 37% wind is preferred by a risk averse investor from a predictability error, contribution to peak demand and LCOE perspective. However, the investor should be aware that this portfolio is not the portfolio with the lowest risk related to volatility. Therefore, the assumption that less volatility causes less balancing costs should be examined in detail based on real market conditions. This might enable investors to evaluate the financial impact of volatility.

4.3. Conclusion

This dissertation combines wind and solar energy and identifies that investing in both technologies decreases risk. Four objective functions are used to determine optimal wind and solar portfolios that are [1] minimizing predictability errors, [2] minimizing volatility, [3] maximizing contribution to peak demand and [4] minimizing levelized cost of energy. This publication borrows an optimization approach to reduce the variability of the objective functions and provides with the underlying model assumptions of normally distributed returns reliable and valid insights into German wind and solar portfolios. A German hourly three-year wind and solar dataset for generation and forecast demonstrates the usefulness of mean-variance portfolio theory for wind and solar portfolio development. Several relevant insights to the current policy debate are determined:

First, it is shown that the empirical German portfolios of 2010 and 2012 are far from the predictability efficient frontier of these years (figure 50). By investing in portfolios that lie on the efficient frontier, there could have been large benefits minimizing the predictability error. From a volatility and contribution to peak demand perspective, the empirical German portfolios lie on the efficient frontier but indicate a high level of risk. This might have been decreased by investing in another combination of wind and solar power. The results are a first indication that early wind and solar investors did not include technological risk in their investment decision since there has been no financial impact on their investment, so far. These findings are important for policy makers to evaluate former policy regulations from an investor risk perspective.

Second, this study finds that each optimization model recommends another composition of wind and solar energy being the ideal portfolio as illustrated in figure 57. Surprisingly, three out of four models propose a share of wind between 35% and 40%. These findings are relevant to the policy debate on supporting the ideal long-term portfolio not only from a technological optimization approach linked to system security but also from a cost efficiency approach.

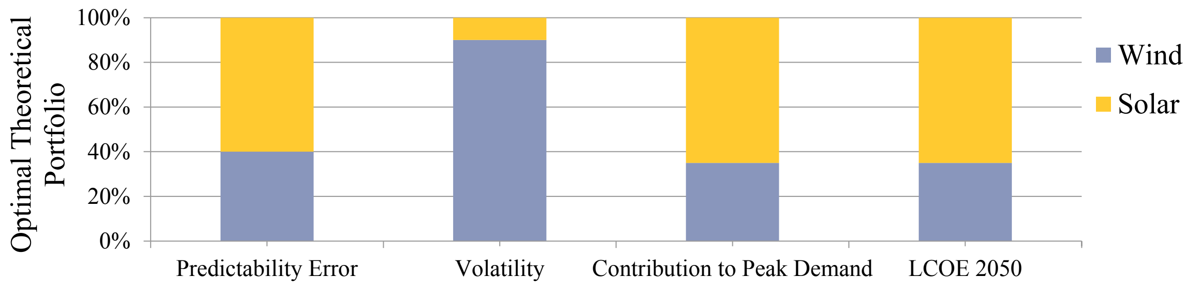

Figure 57: OTP Predictability error, volatility, contribution to peak, LCOE

Third, the results show that from an optimized theoretical predictability error perspective the solar share is higher than the wind share. This can be interpreted by the lower standard deviation which means that solar power is predicted more precisely over the three-year time period. Such findings are not surprising since during night time the predictability error for solar is most often close to zero (figure 28b). On the contrary, the optimized theoretical volatility portfolio advices to hold a higher share of wind. Although wind volatility takes place in more hours than solar volatility (figure 11), the standard deviation indicates that the hourly variation of solar during the day times (figure 43 a), b)) is on average higher than the daily wind variations from one to the next hours. These two objective functions can be interpreted as optimizing for balancing costs. Policy makers should therefore determine which objective is more relevant to decrease balancing costs in the long-term. Regulations might drive investments towards efficient predictability error or volatility wind and solar portfolios.

Fourth, the contribution to peak demand portfolio prefers solar over wind power. A lower solar standard deviation shows that although wind contributes in more hours within the year (figure 12) the variation of the level to which wind contributes is higher than for solar power (figure 38 a), b)). This objective function takes into account optimizing for capacity costs. Thus, the political perspective should consider if this function is relevant in the long-term. In case this applies, the paper suggests to develop regulations that support efficient contribution to peak demand portfolios.

Fifth, the approach of optimizing levelized cost of energy prefers solar power over wind power as long as solar levelized cost of energy is equal or below wind LCOE. Although solar power generates in less hours of the year, the lower solar standard deviation (figure 46) indicates that the level of generation is more consistent in the three-year time period. The fifth objective function can be used to determine the relevance of total system costs. Policy should wisely follow the wind and solar levelized cost of energy development to determine cost efficient long-term portfolios. The level of balancing and capacity costs might limit potential of levelized cost of energy efficiency gains but also create constraints optimizing for predictability error, volatility or contribution to peak demand portfolios.

Finally, integrating all perspectives is essential to develop conditions that lead investors to continue investing in wind and solar power. Ambitious policies might consider introducing incentives to support schemes, such as a feed-in tariff with an additional component that incorporates balancing and capacity portfolio effects. In case such regulations would be implemented, this dissertation suggests for a risk averse investment a portfolio that holds between 35% to 40% wind. This would optimize (a) potential balancing risk based on predictability, (b) capacity risk based on the contribution to peak demand and be the optimal long-term cost efficient portfolio including balancing and capacity costs (c). The results should be considered as recommendations derived from an exploratory approach that identifies ideal wind and solar portfolios based on mean-variance portfolio theory.

5 Final discussion, implications and further research

5.1. Summary of results

The results that have been identified in this exploratory research approach challenge previous findings that focus on technological feasibility of energy systems. These publications mostly determine portfolios based on levelized cost of energy integrating geographical constraints of potential wind and solar locations (FVEE, 2010; ewi et al., 2010; Greenpeace, 2010; Klaus et al., 2010; Nitsch et al., 2010; Hey et al., 2011). The scope of their approaches is not to determine the optimal share between wind and solar including investor risk, e.g. defined as standard deviation but analyze the feasibility of a total renewable energy generation system including all renewable energy sources as well as storage. They illustrate that future renewable energy systems in 2050 might be likely to hold a share of 52% to 80% wind power (as % of installed capacity). The underlying assumptions in their studies are the goal of a 100% renewable energy system, a lower wind LCOE than solar LCOE and the availability of low-priced storage capacity. The high share of wind in their results is mostly based on the assumption of costs being the only measurement that determines the future energy mix.

Differing from other methods, this dissertation examines risk defined as standard deviation of wind and solar characteristics: predictability, volatility and the contribution to peak demand. In the next step, the standard deviation of levelized cost of energy is observed. This research argues that an evaluation of a long-term cost efficient portfolio should not only include return but also the effect of risk. With this underlying assumption, the dissertation treats return and risk as equally important and identifies for three (predictability error, contribution to peak demand, LCOE) optimized portfolios that risk is minimized for a wind share of 35% to 40% and for one ideal portfolio (volatility) for a share of 90% wind.

5.2. Theoretical contribution

The presented research study contributes in five areas. First, to portfolio theory in the energy sector; second, to literature developing future renewable energy scenarios for 2050; third, to literature assessing empirical wind and solar distributions; fourth, to the levelized cost of energy method; and lastly to the political and investor perspective.

5.2.1. Contribution to portfolio theory in the energy sector

With respect to portfolio theory it is the first time, optimized wind and solar portfolios have been developed. Prior research rather focused on either integrating a renewable energy source into a conventional generation portfolio or optimizing the output of several disperse located wind generators. Although existing literature focuses on LCOE or generation output per installed capacity, neither volatility or predictability has been observed in this ways.

5.2.2. Contribution to renewable energy scenario development

One of the major contribution of this work is that the foundation of the research framework seeks to integrate three different perspectives on one renewable energy goal: the political (1), the technological (2) and the investor perspective (3). It summarizes in detail the perspectives and outlines their interaction. The developed research framework combines the elements of the perspectives and advances current approaches by integrating risk. Risk is defined by variability. The findings add to one dimensional renewable energy scenario development and indicate that integrating risk to the analysis changes results, significantly.

5.2.3. Contribution to empirical wind and solar research

With respect to the empirical large sample of German wind and solar generation and forecast data of three consecutive years (2010 to 2012), it is shown that distributions vary from year to year. It is the first time that a study examines skewness and kurtosis for wind and solar distributions for a dataset of a whole country. The insights contribute to wind and solar distribution research and their relationship (Drake & Hubacek, 2007). The existence of skewness and kurtosis challenges the assumption of a normal distribution drawn by prior research that calculates optimized generation portfolios.

5.2.4. Contribution to LCOE method

This dissertation derives based on the integrated framework the assumption that technological characteristics of wind and solar result in additional system security costs. Some literature argue that volatility and predictability create balancing costs (Skea et al., 2008). Others point out that a lower contribution to peak demand results in additional capacity required to maintain the same level of system reliability (Gross et al., 2006). Although existing approaches integrate environmental costs (Jansen et al., 2006; Bhattacharya & Kojima, 2010) for conventional generators, the introduction of system security costs has not been used, so far. Therefore, this dissertation integrates balancing and capacity costs in the LCOE approach.

5.2.5. Contribution to political and investor perspective

In essence, the results of the analysis enables to broaden the discussion of how to reach a specific renewable energy goal. First, it shows not only that an integrated framework is important but also that elements within the framework influence each other and might generate differing results. Second, it raises the awareness that potential additional balancing and capacity costs might occur due to higher wind and solar penetration levels. Regardless of the financial burden for investors or society, it is essential to incorporate them into total system costs to maintain system reliability. Third, not only costs should be regarded when leveraging high wind and solar investments but also risk. Regulatory frameworks that transfer high risk towards investors might lead to financial gaps. Thus, the design of political instruments to enable investments in wind and solar energy have to provide the right level of return and risk. Not only theoretical contributions but also practical values are comprised in the results. Investors, for instance, might not be aware that balancing and capacity costs caused by wind and solar generation might play a role for future investments. New regulations might provide e.g. incentives in case low technological risk is caused by wind and solar installations. The next section draws implications for policy makers and investors.

5.3. Implication for policy maker

This dissertation points out three implications for policy makers. They are mainly derived from the integrated research framework:

1. Use an integrated framework to determine long-term wind and solar portfolios.
The first point refers to the finding that the political, the technological and the investor perspectives influence each other. Thus, it is essential that all perspectives are considered and aligned in order to reach common renewable energy goals.

2. Be aware that the least short-term cost portfolio might not be the least long-term cost portfolio.
The second recommendation is consistent with the findings for LCOE portfolios. The changing optimal share over time indicates that the long-term cost efficient portfolio differs from the short-term ideal portfolio, mainly based on the level of wind and solar LCOE.

3. Provide a stable investment environment to reach renewable energy goals.
The last recommendation is related to balancing and capacity costs. Regulations that do not clearly state who might be responsible to compensate the costs for additional system security costs imply risk for investors. This might negatively impact the investment behavior jeopardizing the ability to reach renewable energy goals.

5.4. Implication for investors

Four implications are drawn for the investor perspective. They relate to risk and the interaction between technological characteristics and system security costs. Four principles are derived:

1. Pick the energy investment portfolio not only based on potential return but also on risk.
This implication relates to the finding that the results differ from approaches taking into account levelized cost of energy only. It appears that changing the view towards a two dimensional approach that includes return and risk generates other results.

2. Use long-term data to evaluate risk.
The second implication is related to the finding that the results based on annual data varies from the results based on three-year data. Hence, longer timeframes are able to balance out individual years that indicate extreme variation. The larger the dataset the better the evaluation of risk.[3]

3. Track regulations related to balancing and capacity costs.
The third recommendation relates to the finding that balancing and capacity costs are sensitive to the ideal investment portfolio. The level of system security as well as the relation between wind and solar balancing and capacity costs are relevant to determine the lowest risk portfolio.

4. Track the development of investment costs.
The fourth point is based on the finding that investment costs are sensitive to LCOE and determine the share of the specific renewable energy source within the portfolio. In addition to this, ongoing technological development might lead to essential price changes within the industry resulting in different optimized long-term portfolios.

[3] Risk is defined as the standard deviation of output

5.5. Limitations and further research

This dissertation applies portfolio theory in the energy sector for one specific country, namely Germany. On the one hand, the large dataset provides an ideal context for detailed empirical analysis covering wind and solar generation and forecast for three consecutive years. On the other hand, the generalization of the exploratory results is only partially applicable to other settings (e.g. different times). Datasets of other countries might show different generation and forecast characteristics, effects generated by disperse locations or differing potential related to both geography and the age of the generation park. Thus, this work is seen as starting point for further research. One might use other datasets and test the applicability of the framework to other country-specific settings.

Moreover, the dataset captures a timeframe of three-years (2010 to 2012). As shown before, the reliability of the results in the long-term increases with longer timeframes. Further studies could add to reliability by collecting generation and forecast data over longer timeframes and assess if results change. This might lead to insightful details related to the assumption of the distributions following the central limit theorem. In addition to this, one may examine the results by using a daytime data set or a nighttime data set only. This might lead to different results and generate detailed information about daily impacts. The same might be performed for seasonal data sets (e.g. summer, winter).

Within the selected timeframe, high installation rates of solar energy have been observed. An interesting observation might be a detailed analysis of the impact of the annual increasing solar energy production on results. Furthermore, the relevance of annual varying weather conditions in 2010 to 2012 might generate interesting findings.

In this dissertation, mean-variance portfolio theory has been used to find optimal wind and solar portfolios. Additional studies might expand this approach by integrating additional renewable energy generators e.g. biomass, hydro power or geothermal. Thus, a theoretical optimal portfolio that includes renewable power generation only could be created.

Using portfolio theory under the assumption of a normal distribution is one major limitation of this study. As discussed in the empirical section, all distributions vary from the normal distribution. Hence, one potentially fruitful area for research might concern the measurement of risk. One could add to the analysis by integrating a third measurement such as skewness (Kim & White, 2004; Canela & Collazo, 2007) or by using proposed distributions such as the Weibull distribution for wind generation (Borchert & Schemm, 2007) or a hybobolic distribution for solar forecasting (Hodge et al., 2011). Moreover, scientists might develop complex simulations that reconstruct wind and solar generation and forecast data. Another approach of capturing risk is an assessment based on different risk measures. One may argue that risk of loss measurements e.g. VaR or CVaR are another way of risk investigation and generate additional findings when evaluating risk (Borchert & Schemm, 2007; Gass et al., 2011). This would uncover the level of risk misinterpretation generated by using the assumption of normally distributed data.

The positive and the negative variance of the technological elements predictability and volatility are assumed to result in the same level of balancing costs. Thus, they are treated as equally unfavorable for the energy system. Further research might tag a price (e.g. based on market conditions) to the level of positive and negative variance of predictability and volatility. By doing so, the technological measurements used in this dissertation for predictability and volatility would be transferred into financial measures. Thus, portfolios that would use inverse balancing costs as return could be computed. The same method could be used to calculate ideal contribution to peak demand portfolios that define return as capacity costs. By assigning capacity costs to the level of contribution to peak demand the technological portfolios would be transferred into financial portfolios.

The levelized cost of energy method has been extended by integrating balancing and capacity costs. Since integration costs related to grid connection and transmission are out of scope, these input variables might be added to a total cost calculation in the future. In doing so, the impact of grid and transmission costs on levelized cost of energy might be revealed.

Balancing and capacity costs are assumed to increase over time based on the penetration level of wind and solar power. However, it indicates that research within this area is very limited. The assumptions drawn in this dissertation are just a starting point for further research. It is shown that balancing and capacity costs have an impact on the optimal wind and solar portfolio in the long-term. Thus, it is essential to assess balancing and capacity costs for wind and solar energy separately related to the penetration level of each generation source and under a country-specific energy system. Such an approach is likely to decreases the uncertainty level of pricing in unconfirmed system security costs. Further analysis might investigate the level of balancing and capacity costs on a short-term or a mid-term bases e.g. minutes or hours. This would lead to more detailed results based on hourly simulations.

The development of optimal LCOE cost portfolios is drawn under the assumption of different wind and solar penetration levels. In 2050, the supposed penetration level is 80% derived of the German defined renewable energy goal. An interesting follow up research could assess if 80% is the ideal level for wind and solar compared to conventional generators.

Overall, it appears that this integrated work combining several perspectives and methodologies is one of the first attempts to evaluate renewable energy goals not only based on costs but also in terms of risk. It is very likely that different input datasets might yield contradictory results. Thus, this dissertation should not only be regarded as a portfolio theory study in the energy sector but also as a starting point calling for further elaboration on integrated energy research.

APPENDIX

Appendix A

	Obs.	Mean	Variance	S.Dev.	Skewness	Ex. Kurtosis	JB
Wind Predictability Error 2010	8,760	-0.0087	0.0018	0.0426	0.2262	3.6025	$4.8116*10^{3}$
Wind Predictability Error 2011	8,760	0.0023	0.0018	0.0421	1.2121	7.5893	$2.3168*10^{4}$
Wind Predictability Error 2012	8,760	-0.0067	0.0013	0.0357	0.6360	3.2531	$4.4532*10^{3}$
Wind Predictability Error 2010 - 2012	26,280	-0.0044	0.0016	0.0406	0.7012	5.3671	$3.3695*10^{4}$
Solar Predictability Error 2010	8,760	0.0078	0.0018	0.0421	1.8732	9.9918	$4.1563*10^{4}$
Solar Predictability Error 2011	8,760	-0.0057	$7.6905*10^{-4}$	0.0277	-1.1066	9.3371	$3.3590*10^{4}$
Solar Predictability Error 2012	8,760	$4.1081*10^{-4}$	$7.2061*10^{-4}$	0.0268	-0.3560	9.5649	$3.3578*10^{4}$
Solar Predictability Error 2010 - 2012	26,280	$8.3294*10^{-4}$	0.0011	0.0334	1.1603	12.9570	$1.8973*10^{5}$

$$S = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^3}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2\right)^{\frac{3}{2}}} \qquad EK = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^4}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2\right)^2} - 3$$

Table 18: Wind and solar predictability error statistics

Appendix A

	Obs.	Mean	Variance	S.Dev.	Skewness	Ex. Kurtosis	JB
Wind Volatility 2010	8,760	$3.1393*10^{-5}$	$2.5411*10^{-4}$	0.0160	0.0402	3.7736	$5.1999*10^{3}$
Wind Volatility 2011	8,760	$-2.1005*10^{-5}$	$2.9784*10^{-4}$	0.0173	0.0139	2.6548	$2.5728*10^{3}$
Wind Volatility 2012	8,760	$-1.9406*10^{-5}$	$3.5245*10^{-4}$	0.0188	-3.6849	126,76	$5.6106*10^{6}$
Wind Volatility 2010 - 2012	26,280	$1.9113*10^{-5}$	$2.8843*10^{-4}$	0.0170	0.0651	3.0128	$9.9574*10^{3}$
Solar Volatility 2010	8,760	$3.8813*10^{-6}$	0.0011	0.0325	0.1690	3.3038	$4.0256*10^{3}$
Solar Volatility 2011	8,760	$2.6256*10^{-6}$	0.0021	0.0462	0.1702	1.7692	$1.1847*10^{3}$
Solar Volatility 2012	8,760	$3.4247*10^{-6}$	0.0024	0.0487	0.1503	1.6255	997.3611
Solar Volatility 2010 - 2012	26,280	$1.0274*10^{-6}$	0.0019	0.0430	0.1668	2.3123	$5.9766*10^{3}$

$$S = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^3}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2\right)^{\frac{3}{2}}} \quad EK = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^4}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2\right)^2} - 3$$

Table 19: Wind and solar volatility statistics

Appendix A

	Obs.	Mean	Variance	S.Dev.	Skewness	Ex. Kurtosis	JB
Wind Contribution 2010	8,760	0.0777	0.0047	0.0685	1.2050	0.8148	235.6926
Wind Contribution 2011	8,760	0.0896	0.0059	0.0754	0.9825	0.0818	141.0109
Wind Contribution 2012	8,760	0.0717	0.0037	0.0610	1.3881	1.8818	412.8991
Wind Contribution 2010 - 2012	26,280	0.0797	0.0047	0.0689	1.1969	0.8318	703.7866
Solar Contribution 2010	8,760	0.0097	2.3763-4	0.0154	2.1825	4.8355	1.5454*103
Solar Contribution 2011	8,760	0.0353	0.0021	0.0457	1.4670	1.3523	380.5129
Solar Contribution 2012	8,760	0.0510	0.0045	0.0668	1.5066	1.4850	414.2406
Solar Contribution 2010 - 2012	26,280	0.0320	0.0026	0.0506	2.1996	4.9077	4.7602*103

$$S = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^3}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2\right)^{\frac{3}{2}}} \quad EK = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^4}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2\right)^2} - 3$$

Table 20: Wind and solar contribution to peak demand statistics

Appendix A

	Obs.	Mean	Variance	S.Dev.	Skewness	Ex. Kurtosis	JB
Wind Generation 2010	8,760	0.1503	0.0018	0.1338	1.5905	2.7907	$6.5358*10^3$
Wind Generation 2011	8,760	0.1813	0.0251	0.1585	1.2622	1.1415	$2.8014*10^3$
Wind Generation 2012	8 760	0.1737	0.0219	0.1480	1.4986	2.1809	$5.0149*10^3$
Wind Generation 2010 - 2012	26,280	0.1684	0.0219	0.1480	1.4498	1.9689	$1.3451*10^4$
Solar Generation 2010	8,760	0.00661	0.0117	0.1083	1.7700	2.2926	$6.4925*10^3$
Solar Generation 2011	8,760	0.0967	0.0219	0.1481	1.4982	1.0975	$3.7168*10^3$
Solar Generation 2012	8,760	0.1073	0.0270	0.1642	1.5275	1.2622	$3.9881*10^3$
Solar Generation 2010 - 2012	26,280	0.0900	0.0205	0.1432	1.6863	1.9704	$1.6706*10^4$

$$S = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^3}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2\right)^{\frac{3}{2}}} \quad EK = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^4}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2\right)^2} - 3$$

Table 21: Wind and solar generation statistics

Appendix B

Covariance Predictability Error	Wind 2010	Wind 2011	Wind 2012	Solar 2010	Solar 2011	Solar 2012	Wind & Solar 2010-2011
Wind 2010	1.000000						
Wind 2011	0.000051	1.000000					
Wind 2012	0.000113	0.000014	1.000000				
Solar 2010	0.000016	-0.000048	0.000001	1.000000			
Solar 2011	-0.000022	0.000035	0.000009	-0.000180	1.000000		
Solar 2012	0.000020	-0.000011	0.000015	-0.000030	0.000069	1.000000	
Wind & Solar 2010 - 2012							-0.000002

Covariance Volatility	Wind 2010	Wind 2011	Wind 2012	Solar 2010	Solar 2011	Solar 2012	Wind & Solar 2010-2011
Wind 2010	1.000000						
Wind 2011	0.000039	1.000000					
Wind 2012	0.000028	0.000043	1.000000				
Solar 2010	0.000036	0.000063	0.000081	1.000000			
Solar 2011	0.000072	0.000059	0.000103	0.001239	1.000000		
Solar 2012	0.000096	0.000119	0.000107	0.001308	0.001961	1.000000	
Wind & Solar 2010 - 2012							0.000067

$$Cov(X,Y) = \sum_{i=1}^{n} \left[\left(r_{xi} - E(r_x)\right) \times \left(r_{yi} - E(r_y)\right) \right] \times p_i$$

Table 22: Covariance predictability error & volatility

Appendix B

Covariance Contribution to peak demand	Wind 2010	Wind 2011	Wind 2012	Solar 2010	Solar 2011	Solar 2012	Wind & Solar 2010-2011
Wind 2010	1.000000						
Wind 2011	0.000063	1.000000					
Wind 2012	-0.000453	0.000276	1.000000				
Solar 2010	0.000110	-0.000047	-0.000110	1.000000			
Solar 2011	0.000082	-0.000439	-0.000263	0.000292	1.000000		
Solar 2012	0.000384	-0.000712	-0.000285	0.000411	0.001929	1.000000	
Wind & Solar 2010 - 2012							-0.000230

Covariance Generation	Wind 2010	Wind 2011	Wind 2012	Solar 2010	Solar 2011	Solar 2012	Wind & Solar 2010-2011
Wind 2010	1.000000						
Wind 2011	0.000521	1.000000					
Wind 2012	-0.000579	0.001107	1.000000				
Solar 2010	-0.001530	-0.001285	-0.001251	1.000000			
Solar 2011	-0.000744	-0.003008	-0.001977	0.013447	1.000000		
Solar 2012	-0.001203	-0.001520	-0.002756	0.014834	0.021269	1.000000	
Wind & Solar 2010 - 2012							-0.0022278

$$Cov(X,Y) = \sum_{i=1}^{n} \left[\left(r_{xi} - E(r_x)\right) \times \left(r_{yi} - E(r_y)\right) \right] \times p_i$$

Table 23: Covariance contribution to peak demand & generation

Appendix B

Corr.Coeff. Predictability Error	Wind 2010	Wind 2011	Wind 2012	Solar 2010	Solar 2011	Solar 2012	Wind & Solar 2010-2011
Wind 2010	1.000000						
Wind 2011	0.009474	1.000000					
Wind 2012	0.074101	0.009362	1.000000				
Solar 2010	0.008764	-0.027165	0.000697	1.000000			
Solar 2011	-0.018257	0.029963	0.008804	-0.154739	1.000000		
Solar 2012	0.017708	-0.009737	0.016035	-0.026960	0.092231	1.000000	
Wind & Solar 2010 - 2012							-0.001473

Corr.Coeff. Volatility	Wind 2010	Wind 2011	Wind 2012	Solar 2010	Solar 2011	Solar 2012	Wind & Solar 2010-2011
Wind 2010	1.000000						
Wind 2011	-0.002945	1.000000					
Wind 2012	0.091652	0.133524	1.000000				
Solar 2010	0.069205	0.113051	0.132344	1.000000			
Solar 2011	0.096953	0.073778	0.119444	0.827629	1.000000		
Solar 2012	0.123310	0.141630	0.117278	0.828569	0.873225	1.000000	
Wind & Solar 2010 - 2012							0.089963

$$\rho_{x,y} = \frac{Cov\ (r_x, r_y)}{\sigma_x \times \sigma_y}$$

Table 24: Correlation coefficient predictability error &volatility

Appendix B

Corr.Coeff. Contribution to peak demand	Wind 2010	Wind 2011	Wind 2012	Solar 2010	Solar 2011	Solar 2012	Wind & Solar 2010-2011
Wind 2010	1.000000						
Wind 2011	0.013463	1.000000					
Wind 2012	-0.114453	0.057736	1.000000				
Solar 2010	0.104677	-0.043974	-0.122007	1.000000			
Solar 2011	0.046381	-0.127524	-0.104146	0.725465	1.000000		
Solar 2012	0.144292	-0.160790	-0.069973	0.675493	0.827074	1.000000	
Wind & Solar 2010 - 2012							-0.066029

Corr.Coeff. Generation	Wind 2010	Wind 2011	Wind 2012	Solar 2010	Solar 2011	Solar 2012	Wind & Solar 2010-2011
Wind 2010	1.000000						
Wind 2011	0.024386	1.000000					
Wind 2012	-0.029032	0.047203	1.000000				
Solar 2010	-0.104768	-0.074880	-0.078013	1.000000			
Solar 2011	-0.037253	-0.128161	-0.090197	0.838344	1.000000		
Solar 2012	-0.054305	-0.058403	-0.113373	0.833983	0.874435	1.000000	
Wind & Solar 2010 - 2012							-0.105073

$$\rho_{x,y} = \frac{Cov\,(r_x, r_y)}{\sigma_x \times \sigma_y}$$

Table 25: Correlation coefficient contribution to peak demand & generation

Appendix C[4]

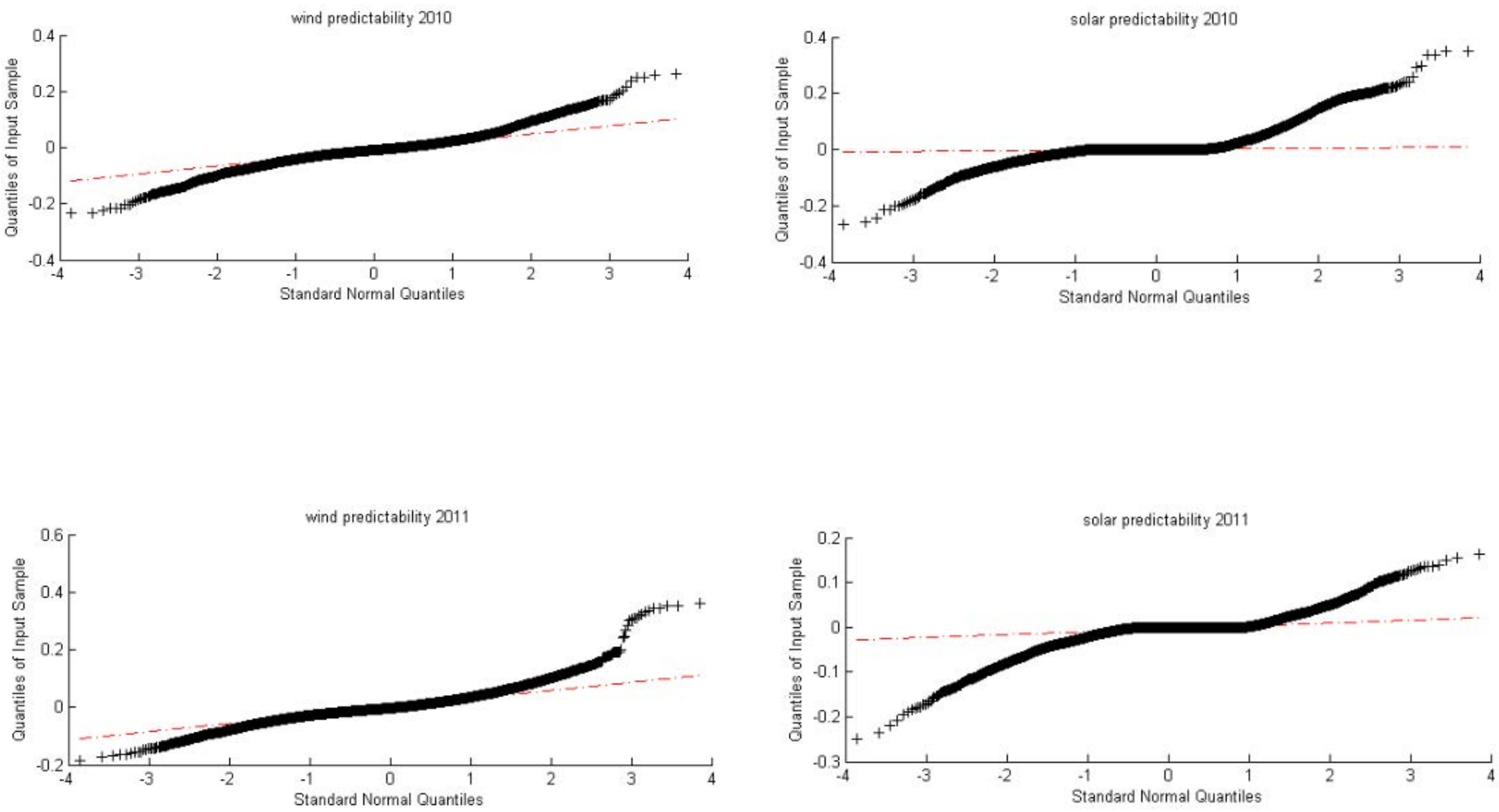

Figure 58: Wind & Solar Predictability Errors QQ-plots 2010, 2011

[4] These plots were developed in cooperation with Sina Marquardt

Appendix C

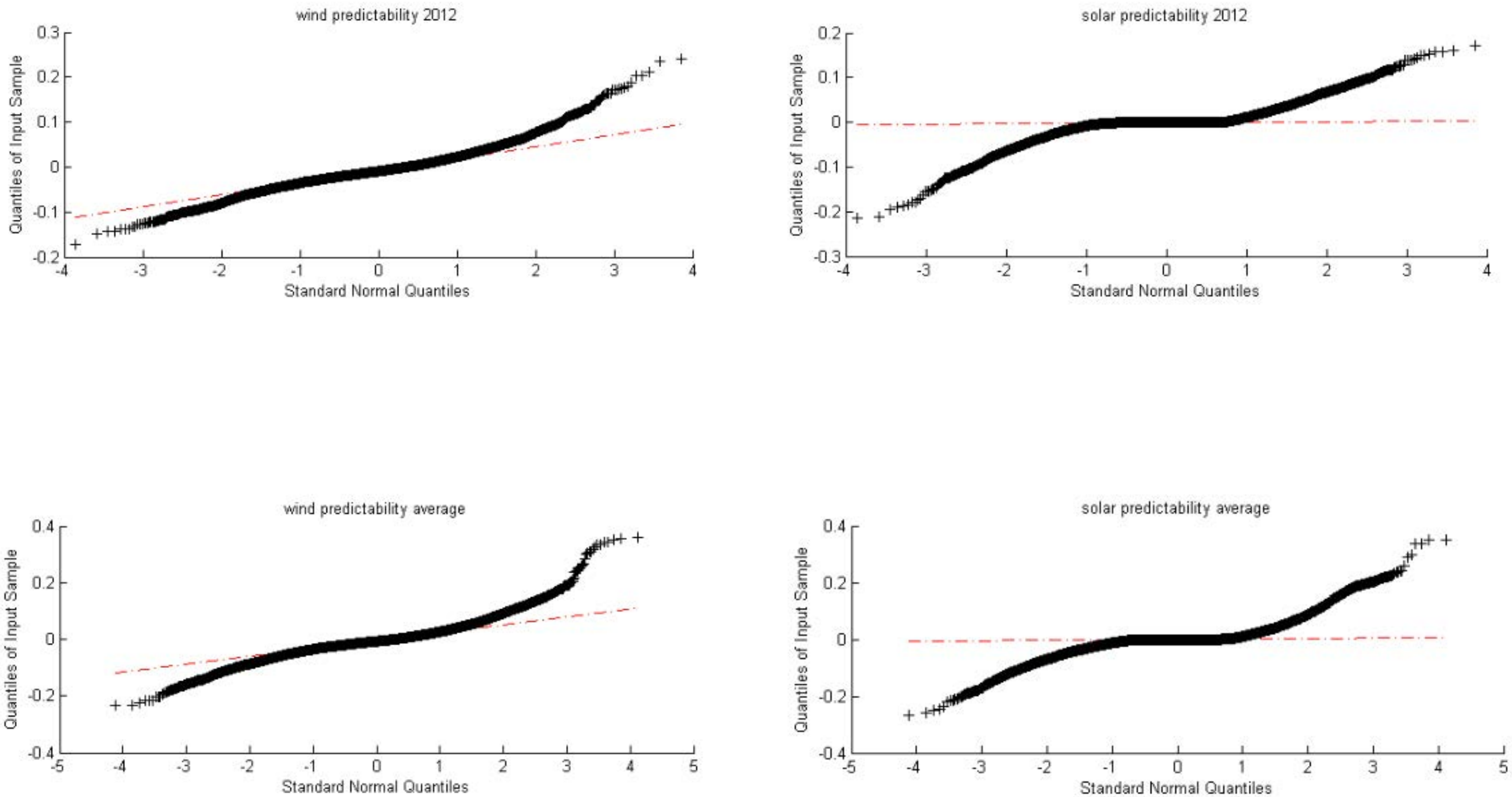

Figure 59: Wind & Solar Predictability Errors QQ-plots 2012, average 2010-12

Appendix C

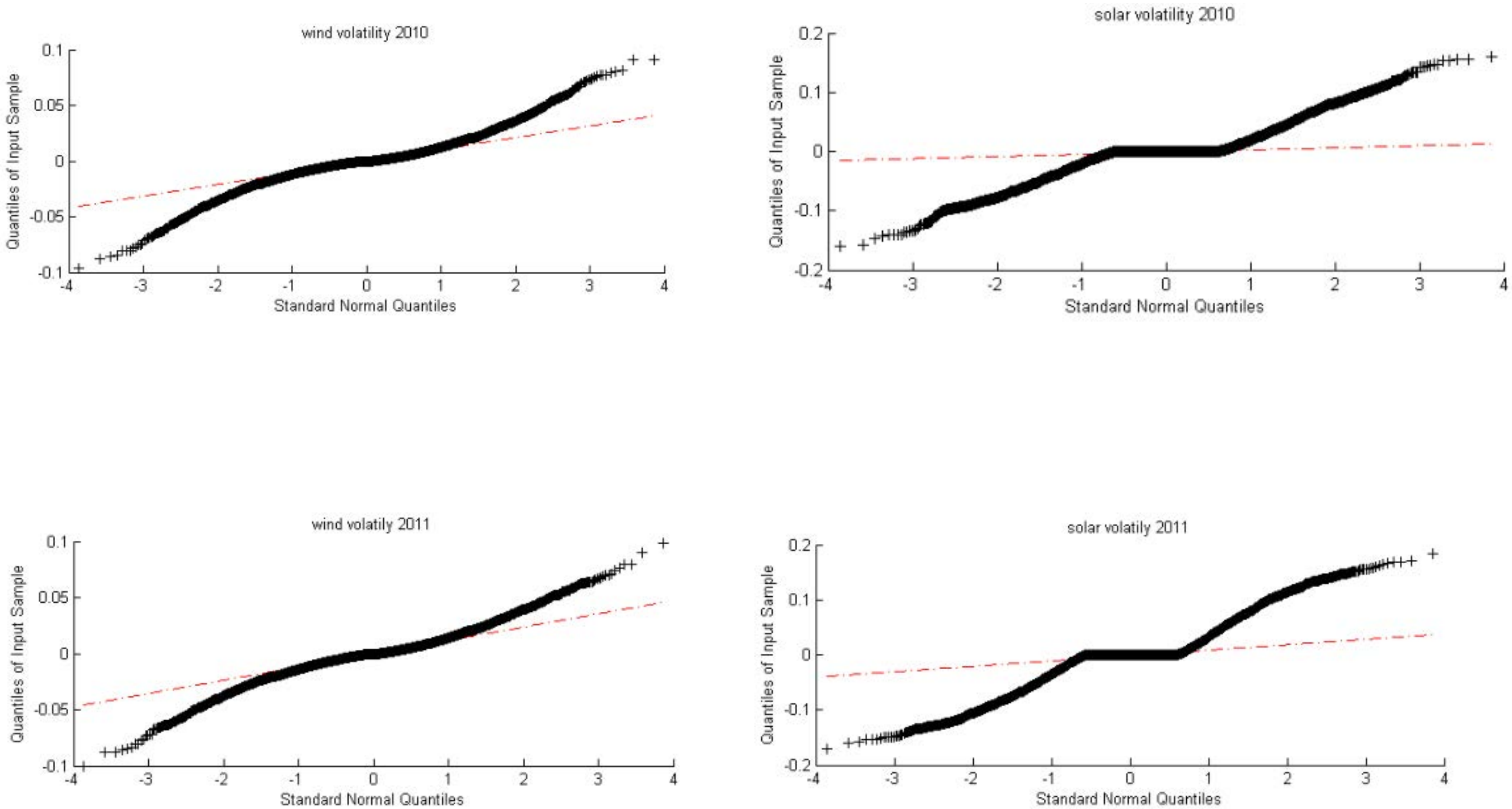

Figure 60: Wind & Solar Volatility QQ-plots 2010, 2011

Appendix C

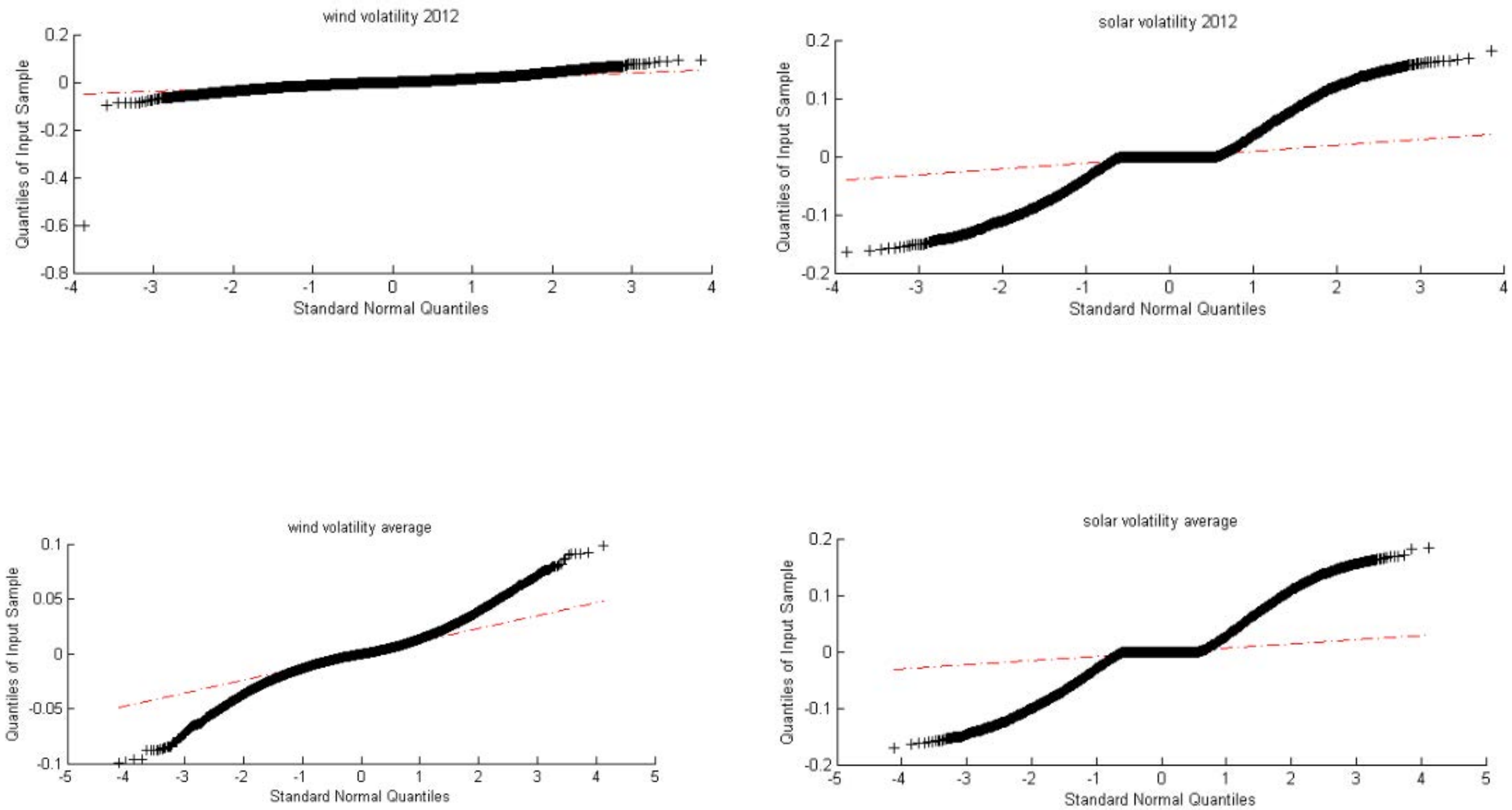

Figure 61: Wind & Solar Volatility QQ-plots 2012, average 2010-12

Appendix C

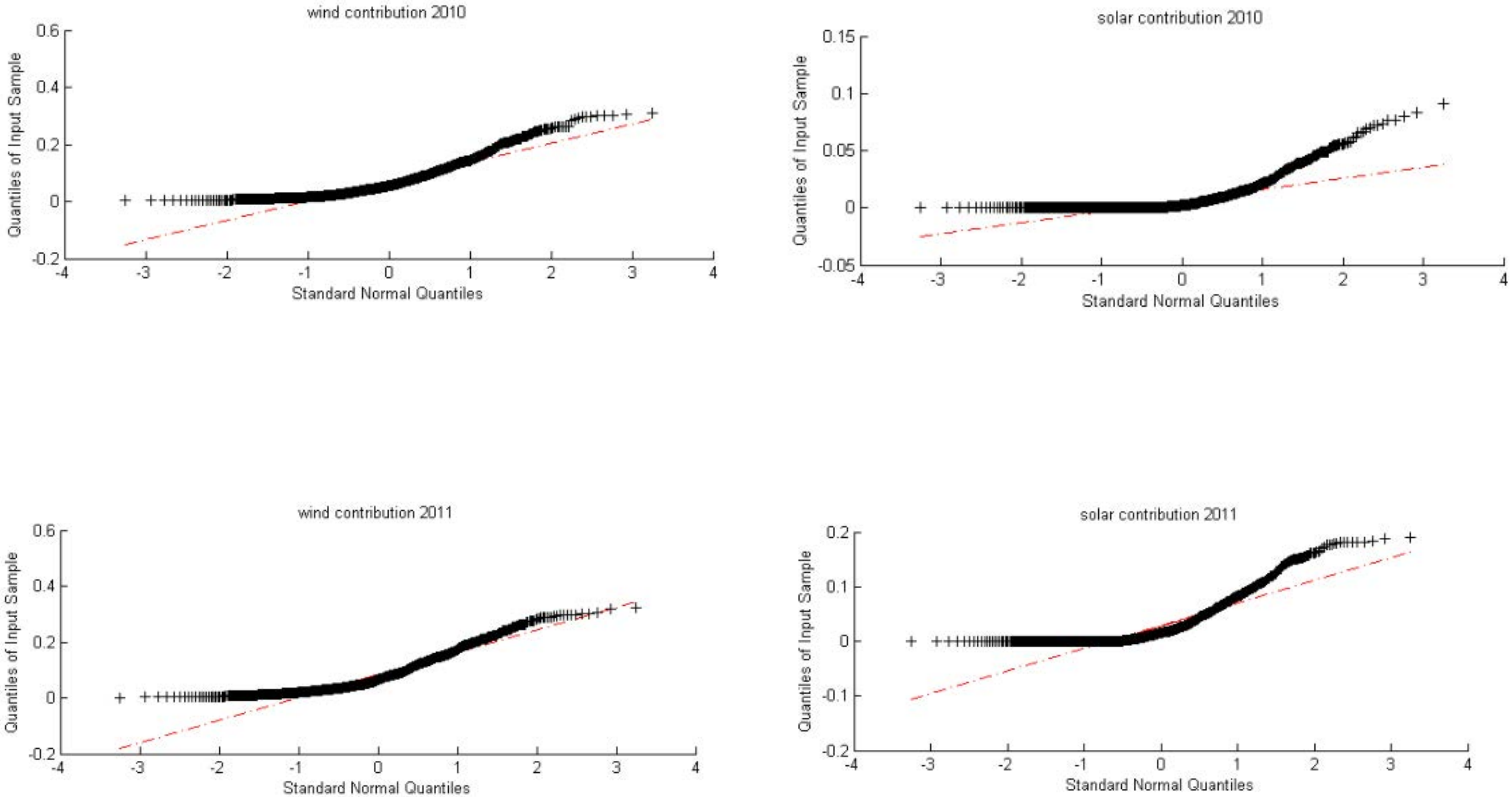

Figure 62: Wind & Solar Contribution to peak demand QQ-plots 2010, 2011

Appendix C

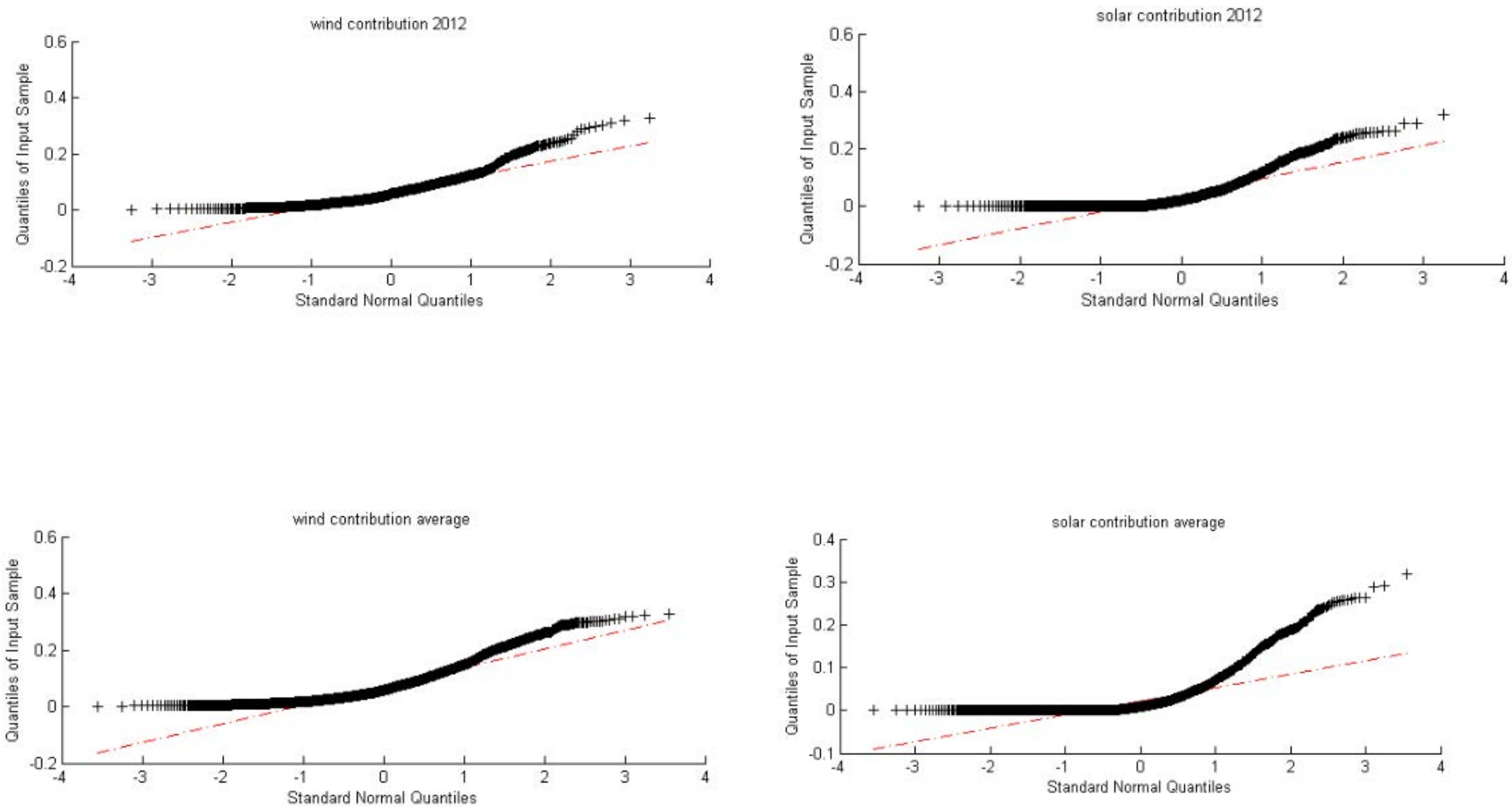

Figure 63: Wind & Solar Contribution to peak demand QQ-plots 2012, average 2010-12

Appendix C

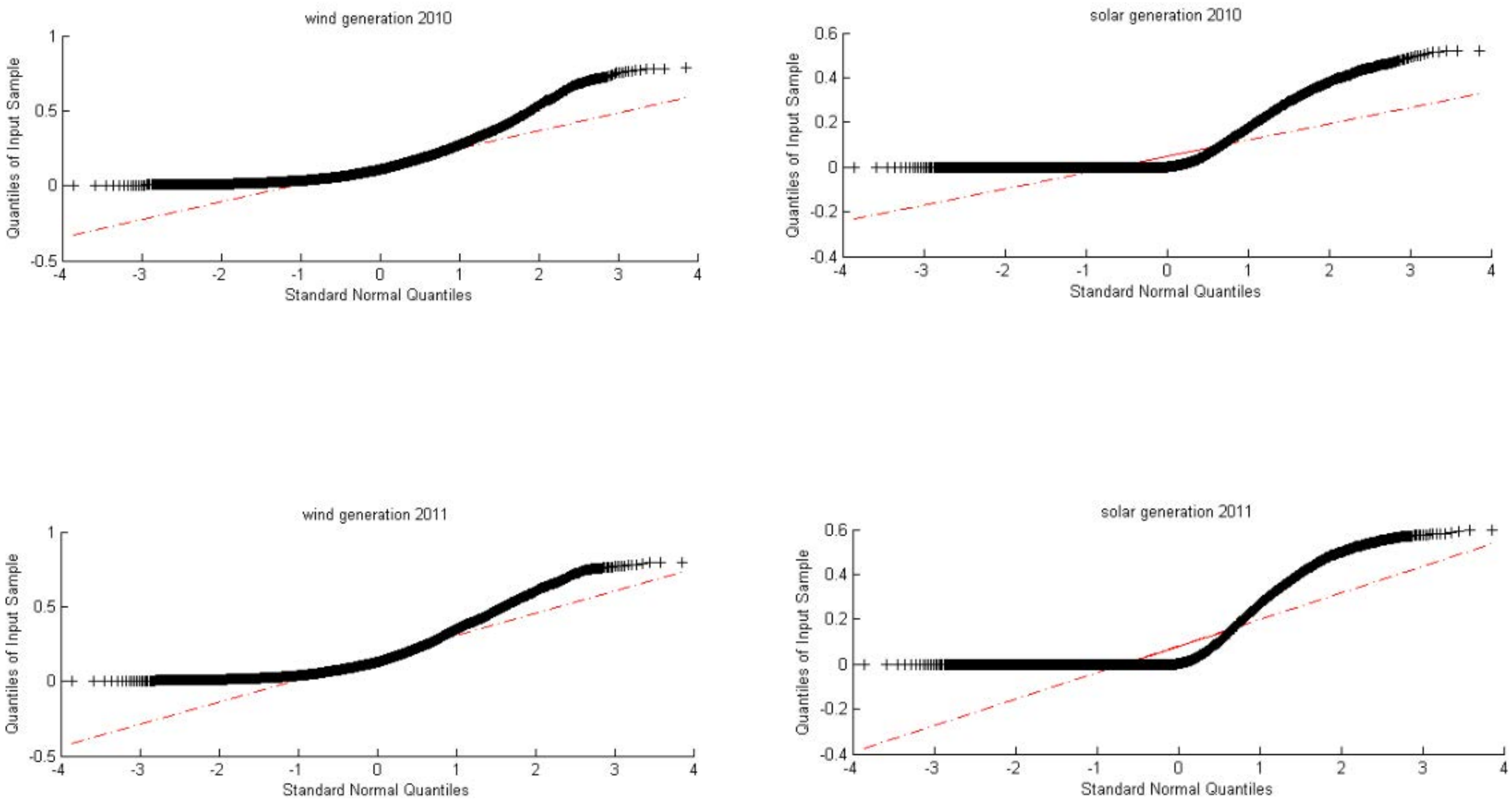

Figure 64: Wind & Solar Generation QQ-plots 2010, 2011

Appendix C

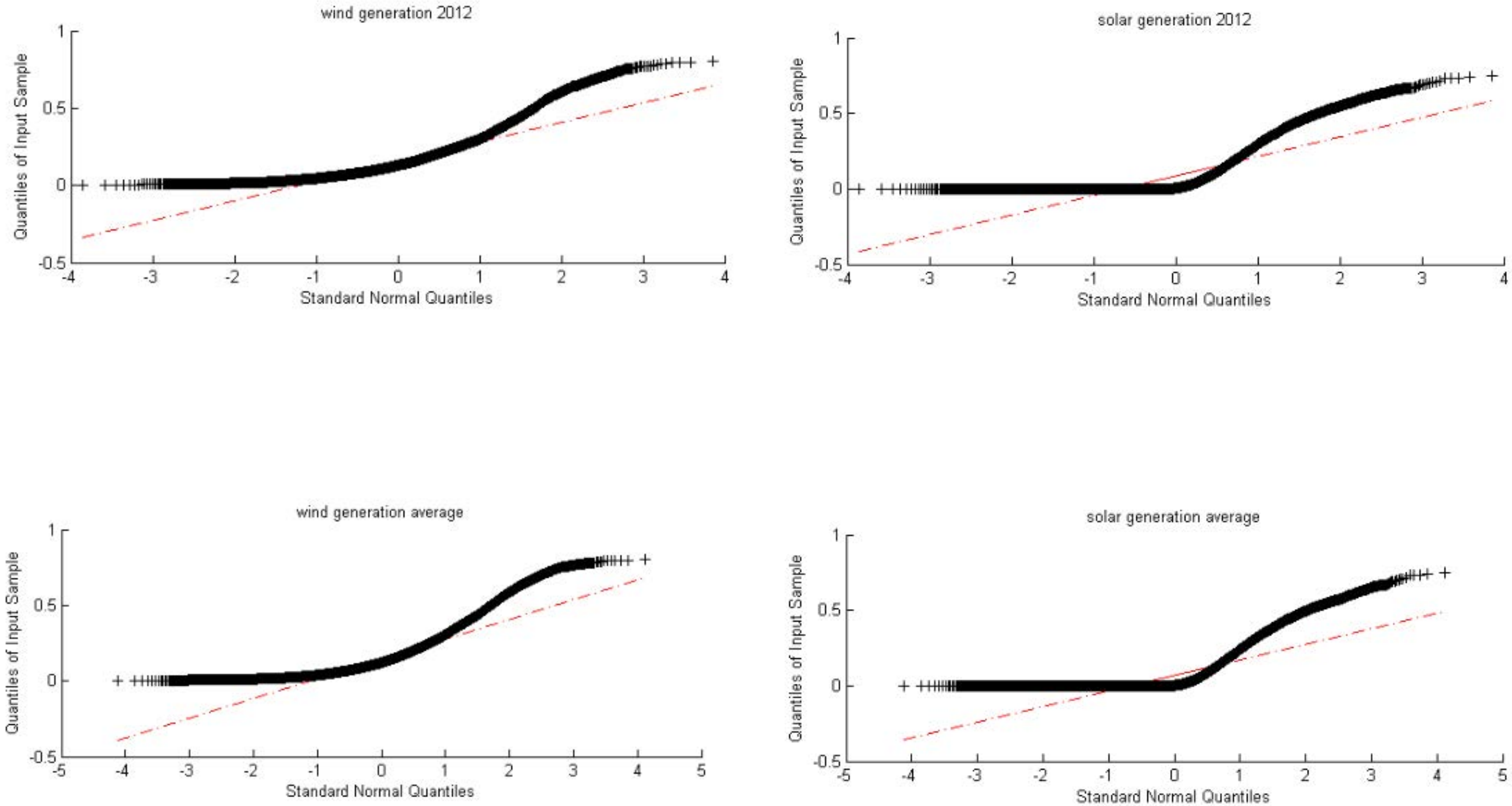

Figure 65: Wind & Solar Generation QQ-plots 2012, average 2010-12

Appendix D

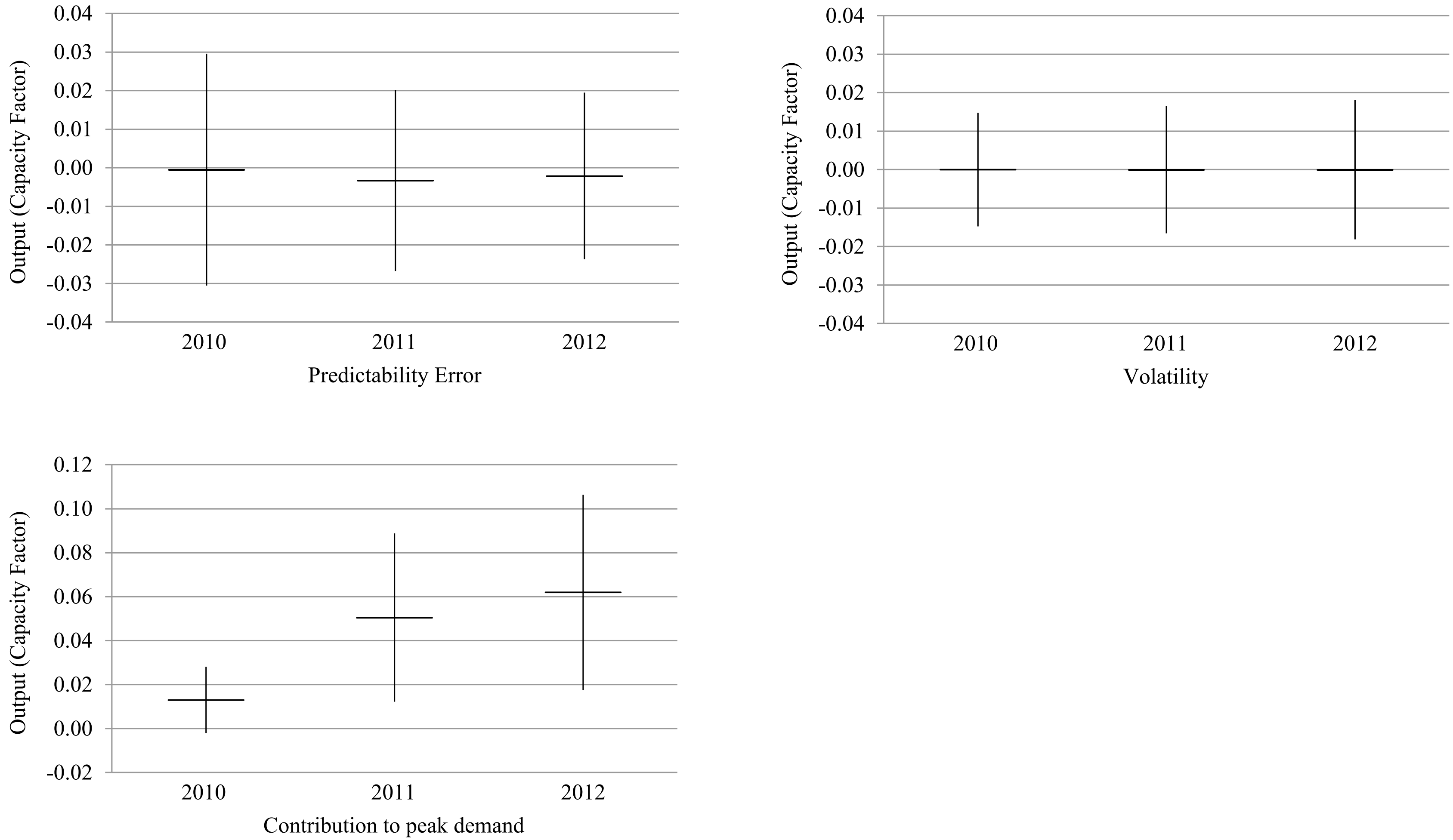

Figure 66: Optimized technological portfolios with results ranging in 2σ

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Curriculum Vitae

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Education

2010 – 2013	**HSG – University of St.Gallen, St.Gallen, Switzerland** Institute for Economy and the Environment Ph.D. in Business Administration/ Strategy Management
2002 – 2008	**University of Stuttgart, Stuttgart, Germany** Institute for Industrial Manufacturing and Management Dipl.-Ing. Mechanical Engineering / Technology Management
2006 – 2007	**Duke University, Durham, United States** Fulbright Scholarship M.E.M Master of Engineering Management

Professional Experience

Since 2010	**juwi technologies, Wörrstadt, Germany** Head of Corporate Development / Renewable Energy Sector
2008 – 2009	**Accenture, Frankfurt, Germany** Strategic Management Consultant / Resources
2005 – 2008	Internships at: **Duke Climate Change Policy Partnership** **Porsche A.G. / Daimler Chrysler Fleetboard**

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Since 2009	**Tropica Verde e.V.,** Frankfurt, Germany Financial Vice President / Environmental Sector

Selection of Publications

11/2012:	**11th Int. Workshop on Large-Scale Integration of Wind and Solar Power – Lisbon** Integration through portfolio approach: Maximizing wind and solar predictability based on German market data 2010-2012 (WIW12-049)
09/2012:	**12th IAEE European Energy Conference – Venice** The impact of wind and solar on peak and off-peak prices – evidence from two year price analysis
11/2011:	**6th Int. Renewable Energy Storage Conference – Berlin** A decentralized approach towards direct renewable energy delivery
08/2011:	**Associated EU Energy Consultants Summer Camp – Meisenheim** Renewable Energy and Market Integration – The EU perspective

Languages

German	mother tongue
Englisch	fluent